Money Matters? Essays on human capital accumulation, occupational choice and worker productivity.

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Declaration of Authorship

I, Joshua J Fullard, declare that this thesis and the work presented in it are my own. I confirm that:

- Chapter 1 is co-authored with Adeline Delavande and Basit Zafar. The other chapters in this thesis are exclusively mine.
- A report based on the findings from Chapter 1 was published in February 2019 and can be found here: https://www.iser.essex.ac.uk/files/projects/information-expectations-transitions-he/information-expectations-transition-higher-education.pdf
- In accordance with the Regulations I have acknowledged any assistance or use of the work of others or any earlier work of my own.

Data Disclaimers and acknowledgment

This work is based on the following datasets:

- Chapter 1 is based on data from the Innovation Panel of Understanding society.
- Chapter 2 is based on data from the Higher Statistics Agency's (HESA) Destination of Leavers Survey and Student Record. This work also uses labour market statistics and the Index of Multiple Deprivation produced by the Office for National Statistics. This work also uses data on teacher vacancies from the Department for Education's (DfE) School Workforce Census (SWC).
- Chapter 3 is based on data from the International Association for the Evaluation of Educational Achievement's (IEA) Trends in International Mathematics and Science Study (TIMSS). This work also uses labour market statistics produced by the Office for National Statistics.

The use of the data in this work does not imply the endorsement of any organization in relation to the interpretation or analysis of the data. All errors are my own.

Dedication

To my family

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Abstract

This PhD thesis consists of three chapters in the topic of applied labour economics. The first chapter investigates the determinants of higher education (HE) participation using new data on university-related subjective expectations elicited from parents and young people in the Innovation Panel of the UK Household Longitudinal Study. We find that differences in HE aspirations can, partially, be explained by differences in the expected returns to a degree and that individuals adjust their university-related beliefs and subjective expectation in response to a light touch information treatment. The second chapter estimates the determinants of occupational choice after graduation. Specifically we look at the effect that labour market conditions have on a graduate's decision to enrol onto an initial teacher training programme (TTP). We find that labour market conditions have no effect on the probability that a graduate will go into a TTP, but heterogeneity analysis suggests that periods of high unemployment impact the composition of graduates who enter the teaching profession. Graduating during a period of low labour demand has an effect on diversity (more male graduates and more ethnic minority graduates), subject specific shortages (more physics graduates) and composition of graduates from different Higher Education institutions. The third chapter analyses whether higher relative wages can motivate teachers to work harder, or more productively, in any way that affects pupil outcomes. Consistent with the predictions of the efficiency wage model, we find that teachers' relative wages have a positive effect on their pupils' cognitive outcomes (measured by test scores), with an effect size similar to a one pupil reduction in class sizes or an additional hours of weekly tuition for a 10 percentage change in relative wages. In addition, we find that relative wages have a positive effect on pupils' enjoyment of learning.

Contents

Introduction

In this thesis I explore the role that pecuniary factors have in determining individual choice behaviour. I test if expected labour market returns affect education and labour market decisions in two distinct contexts and how the pecuniary 'returns to teaching' affect teacher characteristics and teacher productivity.

In my first chapter I test the idea that the expected returns to a degree affect the decision to apply to university. In my second chapter I test the idea that the pecuniary 'returns to teaching' affect i) the decision to enrol onto a teacher training programme ii) the characteristics of trainee teachers. In my third chapter I investigate how the pecuniary returns to teaching affect teacher productivity.

Human capital plays an important role in determining individual and social prosperity. As investment decisions in education differ along socioeconomic lines, understanding the determinants of human capital accumulation is important for achieving a more equitable society where every individual can thrive and prosper regardless of background (Woessmann 2016).

There are several, potentially non-exclusive, reason why young people from less affluent backgrounds are less likely to go to university. Traditional economic models have emphasised the role of resources (e.g. availability of financial aid), information (e.g. about the application process or labour market returns), tastes and preferences for education, as well as genetic factors (Carneiro and Heckman 2002, Dearden et al., 2004, Lochner and Monge-Naranjo 2012). Without data on expectations it is challenging to separate these various explanations as any combination of factors can conceivably be consistent with observed choices (Manski 2004). Yet, the policy implications of these various reasons are distinct. Financial constraints can be alleviated with reduced tuition fees, increased financial aid or easier access to credit. The effect of poor parenting skills and poor home learning environments can be mitigated through high-quality pre-school programmes aimed at boosting cognitive and non-cognitive skills for all children. Unequal access to information can be reduced by targeted information campaigns, as well as mentoring and coaching programmes tailored to disadvantaged students.

In my first chapter I get around the limitations of traditional datasets by using new data on university-related subjective expectations elicited from parents and young people in the Innovation Panel of the UK Household Longitudinal Study. Two unique features of this data are that it i) contains both parents and their own children's subjective expectations ii) we implement a light touch information intervention and evaluate its effect on respondents' accuracy, on the returns to education, and subjective expectations.

Using this new data I am able to add to a long tradition of work seeking to determine whether expectations about future earnings (or about returns to schooling) influence university attendance, field of study or occupation choice (Arcidiacono 2004, Beffy et al., 2012, Berger 1988, Buchinsky and Leslie 2010, Flyer 1997, Willis and Rosen 1979). I also contribute to the growing literature that investigates the role of subjective expectations about the pecuniary returns to education on educational plans or achievement (Delavande and Zafar 2014, Jensen 2010, Wiswall and Zafar 2015a). My work also speaks to the effects of providing information on earnings (Bleemer and Zafar 2018, Jensen 2010, Wiswall and Zafar 2015b) on education-related expectations.

In my first chapter I find that parents/young people who expect higher labour market returns from a degree also expect a higher probability that their child/they will apply to university. I also find that a very light-touch information intervention, showing some statistics about population earnings and employment to families, is powerful enough to change parents' expectations about population earnings so that they become more accurate, with changes still visible 6 months later. This information also increases participants' perceptions about the returns to a degree in the population. However, it does not change parents' perceptions about the future labour market outcomes of their own children. Possibly due to private information, those may be less responsive to general information.

Interestingly, I find that young people's intentions to apply to university are related to their *own* perception of labour market returns to a degree, but not their parents' (once their own is controlled for). However, parents and young people from various SES backgrounds hold similar beliefs about the earnings return and employment returns to a degree and this suggests that it is unlikely that information gaps about the labour market advantage of a degree explains the SES gap in participation.

In the second chapter I investigate whether and how the relative labour market returns to teaching affect the quantity and composition of graduates who enrol onto teacher training programs. Specifically I test the hypothesis that a possible response to graduating during a period of low labour demand is for graduates to sort into teaching – an occupation whose demand is unrelated to the business cycle. However capacity constraints might mitigate the ability of individuals to get access to teacher training placement, so I also investigate if periods of low labour demand affect the composition of those enrolled.

Using rich survey data from the Destination of Leavers from Higher Education (DLHE), my second chapter builds on the existing literature (Chevalier et al., 2007, Dolton and Klaauw 1995, Dolton et al., 2003, Dolton and van der Klaauw 1996, Dolton and Mavromaras 1994) that shows that in England the supply of teachers is sensitive to labour market conditions.

My work is distinct from previous contributions in at least three aspects. First, I consider the current Higher Education environment, with tuition fees and a formal assessment. The existing evidence in England uses data prior to the introduction of tuition fees, when there were no financial costs associated with teacher training, and no cirtification requirements, i.e. applicants did not have to pass a formal assessment. These are two important distinctions as empirical evidences demonstrates that these policies have a meaningful impact on the supply of teachers (Castro-Zarzur et al., 2019, Hanushek and Pace 1995, Manski 1987). Thereofore I would expect the introduction of tutition fees, and certification requirements, to change the relationship between economic conditions and enrolment behavior.

Second, I am able to more precisely estimate the effect of labour market conditions on teacher supply as I observe graduates six months after graduation rather than five to seven years later (Chevalier et al., 2007, Dolton et al., 2003). In England teacher attrition rates are very high, roughly one in three new teachers quit within five years, therefore using data on graduates five to seven years after graduation might be misleading as many teachers will have left the profession by then.

Third, I am able to speak to the effect of low labour market demand on new teachers' composition. Specifically my data allows me to investigate the effect of labour market conditions at entry on the sex, ethnicity, socioeconomic status and educational attainment (degree subject, classification and the quality of institution attended) of the new trainees. As empirical evidence shows that teacher characteristics can affect pupil outcomes (Carrell et al., 2010, Dee 2004, 2007, Egalite et al., 2015, Gershenson et al., 2016), my analysis speaks to the literature which indicates teacher composition is likely to be welfare improving for students (Bietenbeck et al., 2018, Dee 2005, Gershenson et al., 2018, Marcenaro-Gutierrez and Lopez-Agudo 2020). A unique feature of my analysis is that I am able to construct a measure of teacher demand to control for demand-side effects.

I find no evidence that graduating during a period of high unemployment has any effect on the probability that a graduate will enrol onto a TTP. One possibility is that the quantity of graduates who enrol in TTP's might be subject to capacity constraints. However, the composition of trainee teachers might still be affected. Indeed, heterogeneity analysis suggests a compositional effect on the diversity of trainee teachers – with more male graduates, more graduates from an ethnic minority background and more Russell Group graduates as well as a positive effect on subject specific shortages (more physics graduates) – and this is might be welfare improving for students.

While my second chapter investigates if pecuniary factors can affect the composition of the school workforce my final chapter speaks to the strand of literature that investigates if pecuniary factors can be used to motivate existing teachers to work harder, or more productively, in a way that affects pupil outcomes. I use twenty seven years of the Labour Force Survey (LFS) to identify teachers' relative wages and impute these estimates to five waves of the Trends in International Mathematics and Science Study (TIMSS) to estimate the effect of relative wages on pupils' test scores and enjoyment of learning.

With this chapter I intend to contribute to a long tradition of work seeking to determine how higher salaries can affect labour productivity (Akerlof 1982, Fehr et al., 1997, Fehr et al., 2009, Shapiro and Stiglitz 1984) and to the growing literature that investigates the role teacher salaries have on pupil achievement (Britton and Propper 2016, De Ree et al., 2015, Dolton and Marcenaro-Gutierrez 2011, Figlio 1997, Hanushek et al., 1999, Webb and Valencia 2005).

I contribute to this literature in the following ways. First I derive a measure of teachers' relative wages that accounts for differences in job security. This is an important contribution as existing evidence shows that job security plays an important role in the decision to become a teacher and a failure to include this leads to an underestimation of the returns to teaching (Heinz 2015, Priyadharshini and Robinson-Pant 2003). Second, as teachers' salaries are an important policy issue, I also investigate the extent to which teachers are underpaid, relative to their outside option and if teachers who leave teaching tend to sort into higher paying occupations.

Third I use a rich data set that allows me to estimate the effect of teachers' relative wages on tests scores (mathematics and science) and pupil wellbeing, measured by enjoyment of learning. The existing literature has exclusively focused on the effect of teacher's wages on test scores and other measures of cognitive performance (Atkinson et al., 2009, De Ree et al., 2015, Dolton and Marcenaro-Gutierrez 2011, Kingdon and Teal 2007). As teachers play an important role in the development of a wide range of skills understanding the role teachers' wages have on other skills developed in school is an important contribution (Jackson 2012).

Chapter 1

Parental Background, Labour Market Expectations and University Applications Intentions in the UK

With Adeline Delavande[1] and Basit Zafar[2]

1.1 Introduction

There has been a dramatic increase in participation in higher education in the UK. In England, for example, the proportion of 17 to 30 years olds participating in higher education increased from just 5% in 1960 to 49% in 2012, with a strong acceleration in the 1990s (Department for Business Innovation and Skills 2013). A number of studies demonstrate that the expansion of the higher education sector has reinforced rather than attenuated socio-economic inequalities in higher education (Lindley and Machin 2012, Machin and Vignoles 2004). Previous research for the UK suggests that university enrolment (conditional on application) is not related to income once previous achievements are accounted for (Ermisch and Del Bono 2012), but application decisions are (Anders 2012).

There are several (potentially non-exclusive) reasons for the socio-economic (SES) gradient in university applications. Traditional models have emphasised the role of difficulty in accessing credit to explain the gap in enrolment (e.g., Lochner and Monje-Naranjo 2012). However, it is not clear why those gaps are seen in countries where grants and loans are available to students

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from disadvantaged backgrounds. Other factors may correlate with family income: Many studies show high-SES families promote cognitive and non-cognitive skills, have better access to information (which could influence beliefs about available financial aid, the requirements for university admission and the returns to education), and have an increased taste for education or a greater ability to pass on academic ability (Carneiro and Heckman 2002, Dearden et al., 2004). Without data on expectations, it is challenging to separate these various explanations (e.g., Manski, 2004). Yet, the policy implications of these various reasons are distinct. Financial constraints can be alleviated with reduced tuition fees, increased financial aid or easier access to credit. The effect of poor parenting skills and poor home learning environments can be mitigated through high-quality pre-school programmes aimed at boosting cognitive and non-cognitive skills for all children. Unequal access to information can be reduced by targeted information campaigns, as well as mentoring and coaching programmes tailored to disadvantaged students.

In this paper, we use new data elicited from parents and young people in the Innovation Panel of the UK Household Longitudinal Study on: (i) university-related expectations about the chances of qualifying, applying and completing a university degree; (ii) subjective expectations about labour market outcomes conditional on having a university degree or not, (iii) beliefs about population earnings; to (a) provide descriptive evidence on labour market expectations and higher education intentions in the UK and how it varies by family background, (b) assess the accuracy of beliefs, (c) evaluate the relationship between parents and children expectation and, (d) investigate the role of future labour market expectations in the decision to apply to university. Finally, using a randomized information treatment, this paper investigates whether the provision of information on labour market outcomes impacts parents, and young peoples, labour market, and university-related expectations and outcomes.

The differences in expected university outcomes by parental education are clear and large: while 78 per cent of parents belonging to university degree households (i.e. where at least one parent has a university degree) believe their child will have a degree by age 30, only 54 per cent of their counterparts believe so (difference statistically significant at the one per cent level). This difference in expected outcome stems from differences in all the steps of the way toward acquiring a degree: parents from university degree households have higher expectations of the chance of qualifying to go to university (83 vs 65 per cent), the chance of applying if they qualify (83 vs 68 per cent) and the chance of finishing university conditional on going (91 vs 87 per cent). Differences in application expectations persist by household degree status even when financial costs are (hypothetically) forgone. This suggests that there are differences other than financial constraints that explain the gap in expected university outcomes by household degree. While there are also differences in expectations by household income, they are substantially smaller than by household degree. Young people's university-related expectations tend to mirror those of their parents, although children from households with a university degree have slightly lower expectations than their parents, resulting in a smaller gap in expectations by household education.

Respondents perceive overall a positive payoff for their children/themselves to a university degree versus no university degree, both in terms of employment and earnings. For example, Parents expect their children to earn £33,500 per annum on average if they have a university degree, compared to £24,300 per annum without a degree. Interestingly, parents from a high-income household or from a university degree household expect their children to earn significantly more both *with* a degree and *without* a degree than their counterparts. They also expect their children to have a more favourable growth in earnings. As a result, parents from more privileged backgrounds do not expect higher earning returns to a university degree than parents from less privileged background.

These differences in earnings expectations by background could be due to different beliefs about children's ability, or different access to job networks. Interestingly, they do not seem to be driven primarily by differential knowledge of population earnings. To directly test respondents' knowledge, we asked them about the average earnings of current 30 year-olds who have a degree and those of 30 years old who do not have a degree of the same gender as their child. For the population earnings with a degree, parents from all backgrounds tend to have similar, and underestimated, perceptions. Parents from more privileged backgrounds expect slightly larger population earnings without a degree than their counterparts, and are as a result slightly more accurate, as everyone tends to under-estimate those earnings as well. But the difference by parental background in population earnings expectations is small, and more than half the one found for their children's future earnings. Overall, parents under-estimate the population earnings returns to a degree by about £2,000 per annum.

Our focus on the perceived labour market returns to a degree stem from the fact that they ought to be an important driver of the decision to go to university. Indeed, in our data, parents who expect higher labour market returns for their children also expect a higher probability that their child will apply to university. A unique feature of our data is that we have both parents and their own children's subjective expectations. Interestingly, we find that young people's intentions to apply to university are related to their *own* perception of labour market returns to a degree, but not their parents' (once their own is controlled for). However, given that parents and young people from various SES backgrounds hold similar beliefs about the earnings return and employment returns to a degree suggest that it is unlikely that information gaps about the labour market advantage of a degree explains the SES gap in participation.

Half of the households were randomly provided with information about the average annual earnings of men and women aged 26-34 and working full time for university degree holders and for those without a university degree, and their respective employment rate. Households received a mailing with an information sheet just after the baseline interview, and by post again about 6 months prior to the follow-up interview. Those who received the information are more accurate about the population earnings of graduates than those who did not receive information, suggesting information had a positive impact on accuracy of expectations. This increase in accuracy translates into higher beliefs about the population returns to a degree: parents who receive the information expect the population return to a degree to be £2350 larger than parents who did not receive the information (controlling for household characteristics). However, this does not translate into increased returns for their own children, and thus does not change plans to apply to university. Our results are consistent with the idea that parents have private information about their child's future labour market outcomes (e.g., child's ability, job network), such that beliefs about their child are less responsive to information than beliefs about population labour market outcomes.

Our paper belongs to a long tradition of work seeking to determine whether expectations about future earnings (or about returns to schooling) influence university attendance, university field of study or occupation choice (Arcidiacono 2004, Beffy et al., 2012, Berger 1988, Buchinsky and Leslie 2010, Flyer 1997, Willis and Rosen 1979). The prior literature has relied on various types of assumptions (such as myopic or rational expectations) for the mapping between realized earnings and expected earnings. However, existing research from both developed and developing countries has found that individuals tend to be misinformed about the returns to schooling (Betts 1996, Jensen 2010, Wiswall and Zafar 2015a). This has prompted some empirical work on educational choice using expectations data about future earnings. We contributes to this growing literature investigating the role of subjective expectations about the pecuniary returns to education on educational plans or achievement (Delavande and Zafar 2014, Jensen 2010, Wiswall and Zafar 2015a). Our setting is quite unique in that we have expectations of both parents and young people.[3] Parents are likely to be very important in those educational decisions.

Our paper also contributes to a literature investigating the effects of providing information on earnings (Bleemer and Zafar 2018, Jensen 2010, Wiswall and Zafar 2015b) on education-related expectations. For example, Wiswall and Zafar (2015a) find that students at a selective US university are misinformed about returns to college majors, and providing such information impacts intended major choice. Our results suggest that the nature of the expectations (whether it pertains to own child's earning or population's earning) and context might influence how responsive expectations are to new information. In our study, population earnings are more malleable than expectations about own/child's earnings, a result similar Ciancio et al., (2020) who find that population survival expectations are more responsive to information about mortality risk than own survival expectations.

The paper is organised as follows. Section 3 examines the accuracy of parent's labour market expectations while Section 4 investigates the relationship between expected returns and human capital accumulation. In Section 5 we present the effect of providing information about the labour market return to a degree on university-related expectations.

1.2. Descriptive analysis of Subjective Expectations

1.2.1 Sample

The data we use comes from the Innovation Panel (IP) of the UK Household Longitudinal Study (UKHLS).[4] The UKHLS is a longitudinal study that interviews over 40,000 representative households in the UK annually. The IP of the UKHLS uses a sample of 1,500

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[3] Giustinelli (2015) also analyses expectations of parents and young people and studies the joint decision-making. Attanasio and Kaufmann (2014) also have information on mothers and young people's expectations.
[4] University of Essex, Institute for Social and Economic Research. (2019). *Understanding Society: Innovation Panel, Waves 1-11, 2008-2018*. [data collection]. *9th Edition*. UK Data Service. SN: 6849, http://doi.org/10.5255/UKDA-SN-6849-12

households to test innovative ways of collecting data and for developing new areas of research.[5] The innovation Panel sample is a clustered, stratified and equal probability design. The survey is fielded over the phone, internet and face to face. The present paper uses wave 8 (Spring 2015), wave 9 (Spring 2016) and wave 10 (Spring 2017) of the IP where a special module designed by Delavande and Zafar on higher education expectations was fielded. Young people aged 16 to 21 and not currently at university and parents of children ages 10 to 21 were asked a series of detailed questions regarding expected university-related outcomes for themselves or a co-resident child. In addition, half of the wave 8 respondents were randomly provided information about earnings and employment prospects of university graduates and individuals without a degree.

A total of 169 young people and 332 parents participate in the module. We restrict our sample to young people who are under the age of 19 and parents who are responding to questions about children who are under 19.[6] This gives us a sample of 104 young people and 324 parents. The young people are respondents aged between 16 and 18 and are either: not full-time students, or are a full-time student not in higher education. The parents are respondents whose co-resident child is aged between 10 and 18 and in full time education, but not higher education. Sample characteristics are shown in table 1, along with a comparison to the national population of parents of children aged 10 to 18.[7] The IP parents are less likely to be White (71% vs. 76%) and are more likely to be from England (89% vs. 82%) than the population. But they look similar in terms of income and education, with 58% of the IP parents living in a household where at least one parent has a university degree (vs 56% in the population) and 55% of IP parents living in a high income household (vs 55% in the population). Where high income

[5] Understanding society website https://www.understandingsociety.ac.uk/documentation/innovation-panel visited 07/09/2018
[6] This is due to the UK institutional setting. Anyone who is 19 and not in higher education has most likely already chosen not to go into higher education.
[7] Note that the national population of parents aged 10 to 18 is estimated by using a weighted UKHLS sample.

households are defined as those earning more than £3,397 per month, the IP median gross household income. Therefore, as expected, our sample is broadly similar to the population.

Table 1 Distribution of sample across observed characteristics (Percentage)

	(1)	(2)	(3)
	Innovation Panel		Population
	Child+	Parent	
High Income++	58.7	54.8	54.8
White British	78.9	71.2	76.2
Other	17.3	11.8	19.4
Missing	3.8	17.0	4.4
Living in England	96.2	89.2	82.3
HH Degree	53.9	57.9	56.0
Father		37.8	47.5
Male Child	47.1	53.3	
Female Child	52.8	46.7	
Only Father responds	6.7	9.5	
Father and Mother Respond	44.2	58.4	
Only Mothers Respond	35.6	32.1	
No Parent Responds			
	13.5		
Children 18 years old	29.8	7.12	
Parent Over 45		53.3	
Maximum Observations	104	324	29,498

Columns 1-2 report the sample characteristics of the children and parents we use from the Innovation Panel. Column 3 reports the characteristics of the national population of parents of children aged 10 to 18 estimated using the Mainstage of the UK Household Longitudinal Study survey weights. Parents are asked question about their co-resident child.

+We define child as young people who are between 16 and 18 and are in full time education (but not higher education)

++ High income is defined as gross monthly Household earnings greater than the IP median gross household income (£3397 per month or around £41k p.a.)

1.2.2 Overview of the Expectations

At waves 8 and 9 of the IP, respondents are asked a series of university-related expectations. Most questions are elicited using a percent chance format on a scale from 0 to 100%. The detailed wording of questions is presented in Appendix A1 and summarized as follows:

(1) *Expectations of university-related outcomes*: the percent change of (i) having a degree by age 30, (ii) gaining the qualifications to go to university; (iii) applying to university conditional on gaining the required qualifications; (iv) applying to university if all costs were forgone via a scholarship; and (v) graduating conditional on going to university;

(2) *Expected labour market returns to a university degree*: expected earnings at age 30 and 45 conditional on working full-time and conditional on (i) going to university and (ii) not going to university; and the percent chance of being employed at age 30 conditional on (i) going to university and (ii) not going to university;

(3) *Knowledge about labour market returns to a university degree:* population earnings of 30-year old of the respondent's (or child's) gender with and without a degree.

(4) *The expected monetary cost of going to university:* Expected tuition and expected loan.

An overview of respondents' expectations is presented in Table 2 (parents) and 3 (young people). Response rates are high (above 87% for parents and children), except for the monetary cost of going to university where they are 10 to 20 percentage points lower. Parents report on average a 68% chance that their child will have a university degree by age 30. The differences in expected university outcome by parental education are clear in the very first question: while 78 percent of parents belonging to university degree households believe their child would have a degree by age 30, only 54 percent of their counterpart believe so (difference statistically significant at the 1% level). This difference in expected outcome stems from differences in all the steps to acquiring a degree but is larger for the expectations related to the application process - parents from a university degree household have higher expectations for the chance of qualifying for university (83 vs 65%) and the chance of applying conditional on qualifying (83 vs 68%) – than the chance of finishing university conditional on going (91 vs 87%) where the latter is not statistically significant in a multivariate regression (row 5 table 4).

The differences in expectations related to the application process may reflect the fact that young people from less affluent backgrounds are less likely to study academic post-16 qualifications (i.e. A-levels) and those who do are more likely to study subjects that are not as valued by university admissions.[8,9] In addition, young people from less affluent backgrounds tend to have lower levels of attainment (Gill 2018, Tuckett et al., 2021).[10] Taken together this means that young people from the least affluent areas are almost three times less likely to be accepted onto a university place than their more affluent peers.[11]

Differences in application expectation persist by household degree status even when costs are forgone - parents from a household with a degree report a 13 percentage point higher probability of applying with a scholarship and 15 percentage point without. These relationships continue to hold in multivariate regressions (table 4). This suggests that there are differences other than financial constraints that explain the gap in expected university outcomes by household degree. While there are differences in expectations by household income, they are

[8] In the UK many undergraduate courses require certain grades in certain subjects (i.e. most economics programmes require an A in A-level maths). The more ‘facilitating subjects’ a young person studies at A-level the more undergraduate courses will be available to them. These subjects are maths, sciences, modern and classical languages, English literature, history and geography (Group 2011). Young people from less affluent background are less likely to study these subjects.

[9] For example young people from more affluent backgrounds are more likely to choose subjects in science, maths and languages while those from less affluent backgrounds are more likely to choose subjects in vocational or newer humanities fields such as citizenship, film studies, health and social care, media studies and travel and tourism (Rodeiro 2007).

[10] In the UK many undergraduate courses require certain grades in certain subjects (i.e. most economics programmes require an A in A-level maths). The more ‘facilitating subjects’ a young person studies at A-level the more undergraduate courses will be available to them. These subjects are maths, sciences, modern and classical languages, English literature, history and geography (Group 2011). Young people from less affluent background are less likely to study these subjects.

[11] The 2015 UCAS end of Cycle Report.

substantially smaller than by household degree. In fact, with the exception of the expectations to apply to university, parents from high and low income households do not have statistically different expectations for their children. Regarding gender differences, parents of girls tend to have slightly more positive expectations about university-related outcomes than parents of boys, although the differences are spastically significant only for the chance of qualifying to university. Young people's university-related expectations tend to mirror those of their parents, although children coming from households with a university degree have slightly lower expectations than their parents, resulting in a smaller gap in expectations by household education.

Table 2. Parents' subjective expectations, wave 8

			Child Sex		Household Income		Household Education	
Variables	Mean (£1k's or %)	Response Rate (%)	Female	Male	Low	High	No Degree	Degree
Chance of a Degree by 30	68.02	95	70.2	66.1	64.4	70.7	54.4***	77.8
Chance Qualify for University	75.63	95	79.4**	72.2	73.0	77.6	65.1***	83.2
Chance of Applying to University	76.93	96	78.3	75.7	73.0*	79.9	68.3***	83.2
Chance of Applying With Scholarship	82.45	96	83.9	81.2	80.8	83.7	75.2***	87.5
Chance Finish University	89.59	96	91.5	87.8	89.2	89.8	86.9*	91.1
Childs Expectations								
Expected Earnings at 30 With Degree	33.49++	87	31.3***++	35.4++	32.1*++	34.5++	30.7***++	35.2++
Expected Earnings at 30 No Degree	24.31	87	22.8***	25.6	23.0**	25.3	21.9***	25.9
Expected Returns to a Degree 30	9.80	83	9.9	9.7	10.1	9.6	10.2	9.6
Chance Employed With Degree	91.40	93	92.1	90.8	91.0	91.8	90.0	92.3
Chance Employed With No Degree	86.83	93	88.8	85.1	87.5	86.3	86.4	87.2
Expected tuition	7.05	78	7.19	6.92	6.78	7.23	5.99**	7.56
Expected Tuition England Only	7.48	78	7.33	7.61	7.44	7.50	6.56**	7.91
Expected Loans	7.55	68	7.94	7.23	7.51	7.58	6.60	8.05
Population Beliefs								
Expected Earnings at 30 With Degree	32.04++	89	30.7***++	33.2++	31.2++	32.7++	31.7++	32.3++
Expected Earnings at 30 No Degree	22.10	89	20.7***	23.3	21.1**	22.9	21.2*	22.8
Expected Returns to a Degree at 30	9.910	83	9.9	9.9	10.3	9.6	10.6	9.4
Maximum Observations	323		151	172	146	177	136	187

Stars indicate statistical significances at the 10%(*), 5% (**) and 1% (***) levels. The Plus's indicate statistical significance between the 'with, and without, a degree' labour market outcomes at the 5% (+) and 1% (++) levels. For example the +'s next to the expected earnings at 30 with degree mean that the respondents expected earnings with a degree is statistically different from their expected earnings without a degree at 30.

Table 3. Young people's subjective expectations, wave 8

Variables	Mean (£1k's or %)	Response Rate (%)	Sex: Female	Sex: Male	Household Income: Low	Household Income: High	Household Education: No degree	Household Education: Degree
Chance of a Degree by 30	65.25	93	66.3	64.2	62.1	67.6	59.1	70.3
Chance Qualify for University	71.42	95	71.7	71.2	73.2	70.1	65.1*	77.0
Chance of Applying to University	72.48	96	73.1	71.7	71.1	72.9	69.7	75.1
Chance of Applying With Scholarship	80.39	96	81.2	79.3	79.0	81.3	81.6	79.2
Chance Finish University	87.56	98	88.6	86.4	89.4	86.3	88.0	87.2
Own Expectations								
Expected Earnings at 30 With Degree	36.21^{++}	92	34.2^{++}	38.4^{++}	34.8^{++}	37.2^{++}	36.7^{++}	35.7^{++}
Expected Earnings at 30 No Degree	26.57	91	24.1*	29.3	26.0	27.0	27.5	25.8
Expected Returns to a Degree 30	8.9	84	9.8	8.0	8.8	9.0	8.8	9.0
Chance Employed With Degree	88.73	98	89.0	88.4	90.0	87.8	86.3	90.7
Chance Employed With No Degree	82.10	92	79.3	85.5	85.1	79.9	83.0	81.3
Expected tuition	7.69	73	7.8	7.6	7.2	8.0	9.6***	6.3
Expected tuition England Only	7.82	73	7.8	7.8	7.5	8.0	9.56**	6.5
Expected Loans	7.42	63	7.6	7.2	8.6	6.6	8.7	6.3
Population Beliefs								
Expected Earnings at 30 With Degree	31.22^{++}	88	30.4^{++}	32.1^{++}	29.8^{++}	32.3^{++}	30.3^{++}	31.2^{++}
Expected Earnings at 30 No Degree	22.67	88	21.7	23.8	22.3	23.0	21.8	23.5
Expected Returns to a Degree at 30	8.53	88	8.7	8.4	7.5	9.4	8.4	8.6
Maximum Observations	104		55	49	39	65	49	55

Stars indicate statistical significances at the 10%(*), 5% (**) and 1% (***) level. The Plus's indicate statistical significance between the 'with, and without, a degree' labour market outcomes at the 5% ($^{+}$) and 1% ($^{++}$) levels. For example the +'s next to the expected earnings at 30 with degree mean that the child's expected earnings with a degree is statistically different from their expected earnings without a degree at 30.

The expected labour market returns to a degree are theoretically an important driver of the decision to go to university. We define three measures of returns to a degree:

- *Earnings returns at age 30*: $w_{degree} - w_{no\ degree}$ where w is the expected earnings at age 30.
- *Employment returns at age 30*: $P(job|degree) - P(job|no\ degree)$
- *Labour market returns at age 30* of going to university. If a young individual goes to university, she faces some uncertainty about whether she will complete her studies, and whether she will be employed conditional on completing her degree. Assuming for simplicity no earnings if unemployed, her expected earnings at age 30 are thus given by $P(graduate)P(job|degree)\log w_{degree} + \left(1 - P(graduate)\right)P(job|no\ degree)\log w_{no\ degree}$. If she does not go to university, her expected earnings at age 30 are given by $P(job|no\ degree)\log w_{no\ degree}$. The overall labour market returns to a degree are the difference between those expected earnings given by: $P(graduate)(P(job|degree)\log w_{degree} + (1 - P(graduate)\ )P(job|no\ degree)\log w_{no\ degree} - P(job|no\ degree)\log w_{no\ degree}$.

The first measure focuses on returns in terms of earnings only; the second measure focuses on returns in terms of employment only; the third measure takes into account the uncertainty associated with graduating and finding a job.

Revisiting table 2 we see that parents perceive overall a positive payoff for their children to a university degree versus no university degree. They expect their children to earn £33.5k p.a. on average if they have a university degree, compared to £24.3k p.a. without a degree. They also perceive a benefit in terms of employment probability at age 30 (91% with a degree versus 87% without). Parents from a high income household or from a university degree household expect their children to earn significantly more with a degree *and* without a degree than their counterparts. They also expect their children to have a more favourable earnings growth. These differences in earnings expectations are quite large and significant (e.g., £4.5k p.a. with a degree and £4k p.a. without a degree at age 30). However parents from more privileged backgrounds do not expect higher earning returns (differences in earnings with a degree and without a degree) than parents from less privileged backgrounds. Similarly, there are no differences in the overall labour market return to a degree (see table 4, column 9).

This difference in earnings expectations with and without a degree could be due to different beliefs about children's ability, or different access to job networks. Interestingly, these differences do not seem to be driven by a difference in knowledge on the population earnings returns to a university degree. To directly test respondents' knowledge we asked them about the average earnings of current 30 years old, who have a degree, and those of 30 years old who do not have a degree. For the population earnings of graduates, parents from all backgrounds tend to have very similar perceptions. The difference in population earnings without a degree between high and low income (resp. household with a degree and without a degree) are statistically significant but small in magnitude, resulting in no statistically significance differences in the earnings returns. See also results in table 4, column 11. We investigate the accuracy of beliefs in more details in section 3.

Parents of male children expect higher earnings than those of female children, consistent with the gender pay gap. These differences by child's gender are still statistically significant in a multivariate regression (Table 4, columns 6 and 7). Note that these differences hold for earnings both with and without a degree, resulting in no differences in the returns to a degree by gender.

Table 4. Parents Subjective Expectations on observable characteristics, OLS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	University Related Expectations					Labor Market Expectations			Expected Costs	
	Chance Degree 30	Pr Qualify for University	Pr Apply	Pr Apply With Scholarship	Pr Finish University	Labor Market Returns age 30 Own Child	Earnings Returns at age 30 Population	Pr Emp With Degree Own Child	Expected Tuition	Expected Loan
Child 15 or over	1.307	-1.708	5.878	0.366	2.042	0.347*	1433.1	-0.970	-310.6	598.0
	(4.661)	(4.314)	(4.134)	(4.267)	(3.151)	(0.192)	(1007.3)	(2.182)	(630.2)	(1061.2)
Parents Over 45	1.256	2.173	1.182	0.00533	0.517	-0.119	-3800.8***	1.189	1216.4**	-354.3
	(4.657)	(4.552)	(4.098)	(4.285)	(3.531)	(0.187)	(1022.8)	(2.345)	(603.4)	(1117.6)
Male Child	-5.137	-7.745**	-3.128	-3.544	-3.435	0.237	221.7	-1.672	-230.3	-824.3
	(4.170)	(3.726)	(3.849)	(3.796)	(2.613)	(0.215)	(978.2)	(1.903)	(604.6)	(1127.7)
Male Parent	-4.262	-1.746	1.792	-1.665	0.967	-0.216	1510.6*	-1.942	-664.8	397.2
	(2.754)	(2.432)	(2.924)	(2.928)	(1.904)	(0.184)	(889.1)	(1.879)	(518.5)	(1044.5)
HH Degree	19.89***	14.92***	13.32***	11.44**	2.705	-0.141	-1145.6	2.858	2381.7***	1156.3
	(5.150)	(4.157)	(4.470)	(4.587)	(2.755)	(0.212)	(1030.9)	(2.327)	(631.8)	(1102.5)
High Income	-1.497	-2.727	1.881	-1.906	-2.071	0.290	772.9	0.796	245.5	-890.4
	(4.827)	(4.438)	(4.216)	(4.135)	(3.222)	(0.222)	(1021.5)	(2.394)	(601.8)	(1278.2)
Married	8.268	7.974*	3.035	6.124	3.736	0.232	-1375.8	-1.481	35.96	1023.7
	(5.175)	(4.810)	(4.813)	(4.811)	(3.704)	(0.259)	(1178.7)	(2.715)	(708.2)	(1456.8)
White British	3.589	2.231	-1.494	-4.172	-0.320	0.158	653.9	-1.599	694.4	-919.9
	(5.749)	(5.399)	(4.997)	(4.576)	(3.549)	(0.221)	(1100.5)	(2.939)	(722.8)	(1835.6)
Ethnic Other	11.08	8.076	1.700	0.297	1.912	1.276**	4902.8***	-1.027	169.0	491.1
	(7.745)	(5.811)	(6.160)	(5.899)	(4.107)	(0.545)	(1374.7)	(3.841)	(1099.2)	(2202.5)
England	10.94*	13.36**	-0.864	-1.588	3.221	0.0481	7.834	0.110	2392.2***	3233.4**
	(6.541)	(6.746)	(5.905)	(6.138)	(5.228)	(0.233)	(1336.6)	(3.541)	(793.4)	(1407.6)
constant	41.21***	61.33***	66.22***	80.57***	85.59***	-0.0703	15576.1***	92.86***	211.0	4418.4
	(9.398)	(8.976)	(9.276)	(9.521)	(6.849)	(0.419)	(2148.1)	(4.727)	(991.9)	(3085.9)
R(2)	0.164	0.156	0.102	0.071	0.040	0.094	0.099	0.016	0.116	0.051
DV mean	68.02	75.63	78.36	83.54	89.59	0.613	9909.6	91.40	4501.9	7550.4
N	307	308	275	274	261	221	281	265	324	180

This table presents OLS regressions for the parent's labor market and university relative beliefs and expectations on their observable characteristics. The standard errors are reported in parentheses and the stars indicate statistical significant to our usual levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Ethnicity Missing is our reference category for white British and ethnic other. The standard errors are clustered at the household level. In Column 7 Earnings Returns is defined as expected earnings at 30 with a degree minus the expected earnings with no degree at age 30. Column 6 uses *Labour market returns at age 30* of going to University which takes into account the uncertainty about if they will complete their degree and their employment prospects, conditional on degree attainment. It is calculated by taking the difference between the expected earnings with a degree : $P(graduate)P(job|degree)\log w_{degree} + (1 - P(graduate))P(job|no\ degree)\log w_{no\ degree}$ and the expected earnings without: $P(job|no\ degree)\log w_{no\ degree}$. $^{+}$P>|t| 0.109

Table 5 Childs Subjective Expectations on Observable Characteristics, OLS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
	University Related Expectations					Earnings Expectation For self				Earnings Beliefs for Population			Employment Expectations for Self			Expected Costs	
	Chance Degree 30	Pr Qualify for University	Pr Apply	Pr Apply With Scholarship	Pr Finish University	Exp Earn With Degree 30	Exp Earn No Degree 30	Earnings Returns at age 30	Labor Market Returns age 30	Exp Earn Pop With Degree	Exp Earn Pop No Degree	Earnings Returns at age 30 Population	Pr Emp With Degree	Pr Emp With No Degree	Pr Emp Returns	Expected Tuition	Expected Loan
Male	-0.159	-0.204	0.409	-2.476	-3.261	3710.3	5458.7*	-2069.5	-0.427	1839.3	2309.7	-450.1	-0.0969	5.849	-5.578	-489.7	73.54
	(7.167)	(6.436)	(8.503)	(8.035)	(4.212)	(3744.8)	(3236.7)	(2769.6)	(0.309)	(2408.9)	(1646.7)	(2020.8)	(3.419)	(4.706)	(3.961)	(1054.1)	(1670.9)
High Income	-2.034	-7.306	-3.400	0.390	-1.113	3213.9	821.4	146.5	0.372	1523.3	-107.6	1620.7	-4.432	-6.674	6.234	1082.2	-2863.8
	(7.703)	(6.261)	(9.448)	(8.975)	(3.807)	(3762.1)	(3788.7)	(3419.4)	(0.313)	(2477.5)	(1645.3)	(2099.4)	(3.443)	(4.994)	(4.780)	(1115.4)	(1782.1)
Household Degree	6.455	9.502	4.011	-5.618	-1.176	-1406.4	-2265.1	502.4	0.347	899.9	1209.2	-261.7	3.363	-3.085	3.660	-1836.5	-2611.5
	(8.290)	(7.560)	(8.753)	(7.153)	(4.144)	(3751.5)	(3652.0)	(2086.3)	(0.407)	(2544.3)	(1803.7)	(2361.6)	(3.602)	(5.650)	(5.771)	(1448.8)	(2518.2)
England	18.40	27.18	-23.21***	-9.547	-11.82***	7150.0**	5379.7	186.5	0.129	-3743.7	1611.8	-5377.2	24.39	-16.74***	4.461	5154.0***	8106.2***
	(23.44)	(22.78)	(8.228)	(5.911)	(3.492)	(3130.8)	(3730.9)	(2866.1)	(0.255)	(4673.9)	(2537.5)	(4811.9)	(26.18)	(5.577)	(4.374)	(1094.5)	(2254.0)
British Ethnicity	19.81	15.86**	41.66***	46.29***	22.40***	12883.2*	-5950.8**	9021.9***	0.924**	-1278.8	-6078.1***	4790.7**	12.59	13.14*	-0.0441	1398.8	-1584.0
	(22.46)	(6.898)	(10.38)	(13.97)	(7.008)	(6635.3)	(2950.7)	(2165.7)	(0.392)	(2301.2)	(1450.4)	(1935.3)	(9.678)	(7.132)	(5.771)	(2563.0)	(5285.9)
Ethnicity Other	18.18	7.491	26.75*	37.85**	27.92***	18164.3**	-2621.1	10083.9**	0.999	-2604.0	-6473.6**	3877.2	12.14	11.49	1.964	716.0	1184.8
	(24.67)	(10.10)	(14.97)	(17.58)	(7.692)	(7772.6)	(5582.0)	(4365.5)	(0.603)	(4224.4)	(2739.1)	(3502.6)	(10.44)	(7.711)	(6.900)	(3022.3)	(5580.2)
Parents Married	7.146	7.192	5.456	5.378	-3.935	-1551.1	1150.2	-1604.6	-0.320	1700.9	1558.3	98.23	-0.0431	4.762	-3.976	793.4	2582.9
	(9.690)	(8.410)	(10.09)	(9.084)	(4.424)	(4914.3)	(5432.4)	(3385.7)	(0.515)	(3094.9)	(2107.1)	(2758.9)	(3.990)	(7.123)	(7.739)	(1596.3)	(2743.9)
Constant	23.86	33.58	83.03***	85.79***	109.7***	13597.0	24028.0***	11713.9**	4.670***	30727.3***	24533.5***	8810.7	54.53**	97.03***	1.862	-1590.4	2723.8
	(33.41)	(24.99)	(17.40)	(17.21)	(8.231)	(8710.5)	(5262.0)	(4449.6)	(0.498)	(6005.6)	(3207.6)	(5576.9)	(26.67)	(8.290)	(7.541)	(3099.6)	(3840.2)
R(2)	0.083	0.089	0.137	0.114	0.083	0.068	0.054	0.032	0.082	0.039	0.058	0.045	0.127	0.074	0.071	0.071	0.180
DV mean	65.24	71.42	72.48	80.38	87.56	36209.6	26569.8	8901.1	5.67	31219.7	22674.4	8531.1	88.73	82.10	6.752	4659.6	7417.4
N	97	99	75	75	85	93	93	91	74	91	90	90	90	96	85	104	54

The table presents OLS regressions for the children's labor market and university relative beliefs and expectations on their observable characteristics. We use robust standard errors that are reported in parentheses and the stars indicate statistical significant to our usual levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. We also control for parents marital status missing in our regressions but do not report them in the table above because the quantity of young people in that category is sufficiently small. The reference category for our ethnicity variables is ethnicity missing.

Young people's future earnings expectations are quite similar to those held by their parents when looking at the overall average, but seem more balanced by family background. There are no statistical differences in earnings expectations by household degree or household income in multivariate analysis (table 5). The direction of the heterogeneity in belief is actually reversed in some cases, with young people coming from non-university household expecting on average higher earnings than their counterpart (table 3 and 5), possibly reflecting differences in private information about their future labour market outcomes (i.e. ability, job network). Note however that the sample sizes are quite smaller than those of parents.

When it comes to costs, parents and young people expect to pay between £7.5k on average in tuition per year, and to take loans of a similar amount. Parents from university degree households expect to pay more in tuition than their counterpart, reflecting either differences in knowledge about university tuitions or different expectations in what university their children would attend. In England, tuition fees are capped at £9,250 a year for UK and EU students, with around 76% of all institutions charging the full amount in 2015-16. Contrarily to their parents, young people with no household degree expect to pay higher tuition than their counterparts. Those differences hold in multivariate analysis (tables 4 and 5).

A correlation table of parents' expectations about labour market outcomes is presented in Table 6. As one would expect, the expectations about university-related outcomes are positively related to each other. There is a positive correlation between parents' perceived population earnings and the expected earnings for their children both with and without a degree (correlation of about 0.5). Finally, there is also a positive correlation between expected earning and expected employment prospect (correlation of about 0.17).

Table 6 Pairwise Correlation between parent’s subjective expectations.

Variable	Pr Degree 30	Pr Qualify	Pr Apply	Pr Apply With Sch	Pr Finish	Exp Earn 30 Degree	Exp Earn 45 Degree	Exp Earn 30 No Degree	Exp Earn 45 No Degree	Population Earn 30 Degree	Population Earn 30 No Degree	Pr Emp With Degree	Pr Emp No Degree	Exp Tuition	Exp Loans
Pr Degree 30	1.0000														
Pr Qualify	0.8169*	1.0000													
Pr Apply	0.7925*	0.5193*	1.0000												
Pr Apply With Sch	0.7094*	0.4827*	0.8164*	1.0000											
Pr Finish	0.4622*	0.5974*	0.5773*	0.5851*	1.0000										
Exp Earn 30 Degree	0.1761*	0.2472*	0.1627	0.0869	0.1041	1.0000									
Exp Earn 45 Degree	0.3002*	0.2787*	0.2599*	0.1908*	0.1577	0.7855*	1.0000								
Exp Earn 30 No Degree	0.0915	0.1713*	-0.0349	-0.0601	0.0423	0.5362*	0.3528*	1.0000							
Exp Earn 45 No Degree	0.1470	0.2146*	0.0008	-0.0048	0.0526	0.4791*	0.5211*	0.7734*	1.0000						
Population Earn 30 Degree	0.0389	0.0402	0.0075	-0.0473	-0.0508	0.5407*	0.4534*	0.4426*	0.3518*	1.0000					
Population Earn 30 No Degree	-0.1243	-0.0759	-0.1984*	-0.1967*	-0.0821	0.2503*	0.1396	0.4367*	0.4018*	0.5500*	1.0000				
Pr Emp With Degree	0.2868*	0.3688*	0.3227*	0.2028*	0.4563*	0.1680*	0.1979*	0.1657*	0.2194*	0.1656*	0.1309	1.0000			
Pr Emp No Degree	0.2261*	0.3198*	0.1408	0.0837	0.3661*	0.1246	0.1680*	0.3177*	0.3004*	0.2165*	0.1533	0.6881*	1.0000		
Expected Tuition	0.2172	0.2368	0.1800	0.2443*	0.2248	-0.0784	0.0312	-0.1551	-0.0747	-0.0730	0.0177	0.1608	0.1627	1.0000	
Expected Loans	0.2090	0.1195	0.1743	0.2444*	0.1756	-0.0646	0.1171	-0.1384	-0.0685	0.0117	0.0115	0.1639	0.1215	0.3818*	1.0000

Table shows the pairwise correlations between parent’s university and labour market related expectations for their own child (or population when specified). Stars indicate statistical significant at the 1% level

1.2.3 Link Between Parents and Children's Subjective Expectations

A unique feature of this data is that we have both parents and their child's subjective expectations. Parents are likely to be an important source of information for children. We investigate this relationship in table 7. In every specification we use the child's expectation as our dependent variable and their parents' expectations as our independent variables of interest. We consider the separate effect of mother and father expectations and include missing dummy variables for instances where one of the parents response is missing. These regressions exclude children who have both parents missing (18% of the children's sample).

In terms of university-related outcomes, we find a strong association between the children and parents' subjective expectations. For example, a 10% increase in their father's (mothers) expectations of having a degree by age 30 is associated to a 4.7% (3.0%) increase in their child's beliefs, statistically significant at the 1% level.

Looking at earnings, we find that mother's expectations are positively associated to their child's expected earnings with a degree, while the father's expectations are associated to their expected earnings without a degree. For example, a £100 increase in mothers expected earnings for her child with a degree is associated with a £49 increase in their child's expected earnings for themselves, statistically significant at the 1% level (table 7, column 5). In contrast, there is no relationship between parents and children's expectations about population earning or expected cost.

Table 7. Child's expectations on their parents expectations and observed characteristics (OLS)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
	University Related Expectation				Earnings Expectations for Self		Earnings Beliefs For Population			Employment Exp for Self		Expected Cost	
	Chance Degree by 30	Pr Apply	Pr Apply With Scholarship	Pr Finish Uni	Expected Earnings With Degree	Expected Earnings With No Degree	Expected Earnings With Degree	Expected Earnings With No Degree	Logged Expected Returns	Pr of Emp With Degree	Pr of Emp With no Degree	Expected Tuition	Expected Loan
Fathers Beliefs	0.468***	0.413**	0.460**	0.121	0.228	0.614***	0.158	-0.0707	-0.00901	0.340*	0.187	0.290	0.215
	(0.136)	(0.194)	(0.208)	(0.157)	(0.192)	(0.223)	(0.261)	(0.249)	(0.182)	(0.183)	(0.197)	(0.251)	(1.01)
Mothers Beliefs	0.304***	0.412***	0.217*	0.377***	0.488***	0.342	-0.0838	0.169	-0.0463	0.116	-0.0104	0.0910	0.0286
	(0.112)	(0.133)	(0.124)	(0.112)	(0.183)	(0.272)	(0.161)	(0.121)	(0.188)	(0.137)	(0.135)	(0.205)	(0.18)
Male Child	7.680	2.226	-4.902	-1.144	1049.9	2282.1	-232.8	599.3	-0.350	2.129	8.376*	-173.2	-1275.3
	(7.030)	(7.676)	(7.457)	(4.347)	(3895.7)	(3491.0)	(2763.3)	(2012.1)	(0.383)	(3.214)	(4.765)	(1221.5)	(2095.6)
High Income	-2.183	-6.402	-6.140	-6.053	3631.6	2182.6	1107.8	-286.7	0.231	-4.898	-7.677	1599.8	-2005.7
	(7.347)	(8.008)	(7.922)	(4.383)	(4241.2)	(3654.9)	(2840.6)	(1983.0)	(0.394)	(3.527)	(4.938)	(1295.9)	(2302.1)
HH Degree	-4.156	-8.868	-11.30	-8.003	-6870.0	-5106.7	-1177.8	-104.3	-0.0918	-1.733	-2.050	-1607.1	-1719.7
	(8.063)	(8.471)	(8.359)	(4.957)	(4252.6)	(3791.4)	(2959.8)	(2083.4)	(0.402)	(3.757)	(5.173)	(1365.8)	(2520.2)
England	11.41	-17.62	-12.49	-1.916	6877.7	7845.8	-26.50	2641.8	0.667	-4.840	-16.02	3504.5	5391.7
	(17.68)	(29.75)	(29.26)	(12.40)	(9714.0)	(8732.3)	(6907.3)	(4771.1)	(1.002)	(10.05)	(11.94)	(3322.9)	(7487.0)
White British	57.93*	25.71	23.53	24.09*	28209.7**	-4016.7	-231.7	-6967.0	1.463	31.39***	19.43	2089.1	4668.6
	(31.75)	(21.88)	(21.54)	(13.82)	(13576.5)	(15263.1)	(11853.3)	(8296.6)	(1.445)	(11.12)	(14.77)	(4064.6)	(4800.0)
Ethnic Other	42.16	3.726	6.095	23.76	33960.8**	-3814.5	-1709.2	-8045.1	1.624	31.73***	19.15	-50.40	7121.2
	(32.44)	(23.16)	(22.53)	(14.31)	(14268.8)	(15729.2)	(12225.0)	(8543.1)	(1.542)	(11.63)	(15.52)	(4233.7)	(5209.0)
Constant	-44.99	28.77	46.45	61.12**	-21162.8	2965.7	30655.5**	18699.4**	5.996***	28.78	68.54**	-2846.7	-2895.2
	(40.02)	(37.89)	(38.30)	(23.80)	(20095.4)	(19740.1)	(12823.1)	(8199.2)	(1.173)	(27.55)	(28.17)	(4034.0)	(9813.1)
R(2)	0.352	0.398	0.301	0.345	0.222	0.203	0.098	0.136	0.166	0.250	0.189	0.107	0.165
DV mean	67.94	74.46	81.43	87.58	36080	26658	31537	22679	5.728	89.58	81.82	4600	6841
N	85	69	69	77	80	82	80	79	66	80	84	91	47

The table presents OLS regressions for the children's labor market and university relative beliefs and expectations on their mothers and fathers corresponding labor market and university related beliefs. We use robust standard errors that are reported in parentheses and the stars indicate statistical significant to our usual levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. We also control for parents marital status missing in our regressions but do not report them in the table above because the quantity of young people in that category is sufficiently small. The reference category for our ethnicity variables is ethnicity missing.

1.3 Accuracy of Beliefs

1.3.1 Earnings

We use parents' expectations about current population earnings to assess their accuracy in beliefs. We compare parents' beliefs with population earnings data by gender and degree status from the Labour Force Survey (LFS) Income and Education Analysis using quarterly data between 2004Q2 -2011Q1. The 'True Value' for men is £27,100 with no degree and £39,700 with degree, and £22,600 and £33,800 for women respectively.

We define "error" by subtracting their beliefs from the 'True Value', so a positive (negative) error stipulates that the respondent underestimates (overestimates) population earnings. As the error takes positive and negative values, a mean error of zero does not necessarily represent a low level of error, we also use the absolute value of the error. Parents typically underestimate population earnings, by around £5k with a degree and £3k without (not shown). As a result, parents underestimate the returns to a degree by around £2k. A relatively large standard deviation indicates considerable heterogeneity in beliefs –this is particularly striking for earnings with a degree: the 10th percentile is -£6.2k (-18%) while the 90th percentile is +£13.8k (+37%). Figure 1 presents the earnings return errors and show that about two-third of parent's under-estimate the return to a degree. This is potentially important as we expect earnings return to be important for the decision to apply to university (see also section 4).

We further assess how the accuracy varies by characteristics in a multivariate analysis using the errors and the absolute value of the error (Table 8). We are particularly interested in the difference by households SES status to investigate whether the SES gap in university application may be partly driven by a SES knowledge gap.

Table 8 Accuracy of Parents beliefs (actual – belief) on observable characteristics (OLS)

	(1)	(2)	(3)	(4)	(5)	(6)
	Parents Earnings Errors				Expected Returns Error	
	With Degree		No Degree			
		Absolute Value		Absolute Value		Absolute Value
Child Over 15	-817.5	-653.8	56.21	74.18	-1433.1	-136.9
	(1268.8)	(939.5)	(940.5)	(636.5)	(1007.3)	(696.6)
Parents Over 45	628.5	210.9	-3008.5***	244.4	3800.8***	624.8
	(1293.4)	(908.0)	(963.4)	(692.0)	(1022.8)	(686.8)
Male Child	2964.9***	1387.1*	1693.6*	1137.5**	1178.3	-116.7
	(1055.8)	(723.4)	(888.1)	(570.2)	(978.2)	(697.0)
Male Parent	-308.0	-576.4	671.7	-736.7	-1510.6*	-623.3
	(913.0)	(617.0)	(759.6)	(545.5)	(889.1)	(552.7)
HH Degree	-409.1	-1364.5	-1261.0	-2109.2***	1145.6	-1747.7**
	(1127.0)	(953.3)	(1004.6)	(655.6)	(1030.9)	(778.9)
HH High Income	-2676.5**	-1985.7**	-1771.3	-2237.1***	-772.9	-485.0
	(1341.6)	(988.3)	(1101.0)	(789.7)	(1021.5)	(773.9)
Married	2598.6*	1813.2	1528.5	1497.1*	1375.8	47.79
	(1433.2)	(1132.1)	(1139.7)	(835.1)	(1178.7)	(874.0)
White British	-2612.3**	-800.7	-1325.5	-1062.4	-653.9	568.6
	(1136.4)	(940.1)	(1031.6)	(748.1)	(1100.5)	(736.7)
Ethnic Other	-7124.4***	-621.5	-1852.6	803.2	-4902.8***	1093.7
	(2066.4)	(1178.9)	(1722.9)	(1242.6)	(1374.7)	(1205.4)
England	1010.3	1684.9*	1922.0	-4.300	-7.834	835.4
	(1380.8)	(922.1)	(1543.5)	(1095.8)	(1336.6)	(1088.8)
Constant	5240.9***	7501.3***	3461.2*	7365.5***	-4376.1**	7479.8***
	(1796.2)	(1270.4)	(1957.2)	(1291.2)	(2148.1)	(1694.5)
R(2)	0.110	0.065	0.102	0.121	0.106	0.040
DV mean	4891	7956	2903	5679	2047	6323
N	286	286	284	284	281	281

The table presents an OLS regression of the accuracy of parent's beliefs on observable characteristics. We include Ethnic Missing in our model. We do not report the coefficients in this table as the sample in these categories are sufficiently low. The standard errors are reported in parentheses and the stars indicate statistical significant to our usual levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the household level.

We find a very limited association between SES and accuracy about the earnings returns. High income households appear more accurate about both the earnings with and without a degree, resulting in no difference for the return. Household with a degree appear more accurate about the earning returns without a degree. This does not translate in smaller average error, or more accurate perception according to our accuracy indicator, when looking at the returns (Table 8, column 5). But we do see an effect in the absolute value of the error for returns (Table 8, column 6) suggesting that households with a degree are less likely to make large mistakes in either direction.

We find that parents of male children are more inaccurate than parents of female children about earnings with and without a degree, but the inaccuracy balances out resulting in no differences in the returns. Finally we observe that older parents typically underestimate the expected returns by over £3.8k – driven by the fact that they overestimate earnings without a degree by over £3k.

1.3.2 Employment

Respondents are asked their expectations that their child/they will be employed at thirty both with and without a degree. Unlike for earnings, they were not asked about the current population employment rates so we cannot directly assess knowledge about employment prospects. Nevertheless, it is still interesting to compare current employment rates with employment expectations. Using the LFS, we obtain an employment rate of 97% with a degree at thirty for both men and women, and 92% for men and 93% for women with no degree. Using these figures we construct parent's employment "difference" by subtracting their expectations from the current employment rates. We do not call this an error as the difference may reflect private information respondents have about themselves/their children, beliefs about the economy and future employment rates and errors about the current population unemployment rate.

Table A1 in the appendix shows an average difference of 5.6 percentage point both with, and without, a degree, suggesting that they are more pessimistic for their children's employment than is warranted with the current employment rate. There is however a nontrivial amount of parents who are more optimistic – as indicated by the significantly larger mean absolute value of errors. This is particularly true for difference without a degree where the 50th percentile is -7 and the 90th percentile is +42. Using multivariate analysis we find that these differences do not differ by observable characteristics (table not shown).

1.4 Expected Returns and Expectations of Applying to University

We have focused on the returns to degree as those are thought to be important drivers in the decision to apply to university. We investigate this directly by looking at the relationship between the application intentions and expected returns. Using an OLS specification we find that parent's application expectations are positively associated to their expected returns (Table 9). Moreover, the effect is large. For example, an increase from the 50th to the 75th percentile of expected earnings returns (respondents labour market earning returns) leads to an increase of 31 percentage point in the probability to apply to university (Table 9, column 1). The same increase in labour market returns leads to an increase of 72 percentage points in the probability to apply (Table 9 column 2) while an increase in employment returns by the same proportion increases the probability of applying by 6 percentage points (Table 9, column 3).

Focusing on young people, we find that application expectations are only associated with the expected returns for male children (Appendix Table A2). This is consistent with existing evidence that men's educational decisions tend to be more driven by pecuniary factors (e.g. Malgwi et al., 2005).

Table 9 Parents Applications Intentions (Probability of applying) on their expected returns and observable characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
	Probability of Applying No Scholarship			Probability of Applying Scholarship		
Earnings Returns Aged 30	1.236***			0.936**		
	(0.416)			(0.412)		
Labor Market Returns age 30 of going to University		2.806**			1.607	
		(1.179)			(1.165)	
Employment Returns			0.241*			0.116
			(0.136)			(0.135)
Child Over 15	1.220	3.897	3.487	-3.323	-0.393	-1.290
	(3.897)	(3.607)	(3.920)	(3.884)	(3.579)	(3.897)
Parent Over 45	1.838	4.150	1.593	1.335	3.425	0.653
	(3.934)	(3.619)	(3.984)	(3.926)	(3.588)	(3.955)
Male Child	-1.684	-0.717	-3.758	-0.880	2.358	-2.740
	(3.649)	(3.393)	(3.625)	(3.655)	(3.350)	(3.597)
Male Parent	-0.661	-5.545	0.495	-3.531	-6.708*	-1.492
	(3.772)	(3.491)	(3.819)	(3.771)	(3.450)	(3.790)
HH Degree	8.003*	4.171	8.974**	6.249	1.147	6.739*
	(4.070)	(3.751)	(3.974)	(4.076)	(3.710)	(3.953)
Parents Married	5.825	2.679	1.544	7.723	1.872	4.584
	(4.671)	(4.326)	(4.454)	(4.731)	(4.310)	(4.468)
HH High Income	-2.292	1.899	1.893	-6.009	-0.469	-2.352
	(4.199)	(3.954)	(4.057)	(4.283)	(3.945)	(4.077)
White British	-0.823	2.677	-1.819	-4.192	-0.450	-4.516
	(4.944)	(4.476)	(4.938)	(4.873)	(4.416)	(4.888)
Ethnic Other	3.764	9.234	3.645	2.057	8.857	0.869
	(7.365)	(7.011)	(7.110)	(7.367)	(7.023)	(7.090)
England	-1.511	-3.700	-0.602	2.184	-4.006	-3.512
	(6.217)	(5.965)	(6.295)	(6.339)	(5.895)	(6.375)
Expected Tuition	0.0814	-0.162	-0.166	0.000298	0.000304	0.000343
	(0.465)	(0.427)	(0.483)	(0.000464)	(0.000423)	(0.000479)
Tuition Missing	-10.74*	-1.295	-13.50**	-8.836	2.108	-8.582
	(5.461)	(5.341)	(5.481)	(5.525)	(5.280)	(5.484)
Constant	68.88***	83.65***	78.40***	75.09***	84.22***	86.09***
	(10.03)	(9.246)	(9.439)	(9.312)	(7.860)	(8.618)
R(2)	0.125	0.106	0.127	0.105	0.064	0.084
DV mean	78.37	81.32	77.75	83.49	86.22	83.24
N	226	204	240	223	203	237

The standard errors are reported in parentheses and the stars indicate statistical significant to our usual levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The expected tuition is reported in 1,000's and Ethnicity Missing is the reference category for our ethnicity variables.

Because we have data on parents and children, we can also investigate whose expectations – parents' or own– about the returns to a degree seem more relevant to the child's application intentions. Next we use multivariate analysis regressing the child's application intentions on the child's, mothers and fathers expected returns with our usual controls (not reported). We find that the child's expectations are positively associated to their enrolment probability. There is no statistically significant association between the parents expected returns and the child's application intentions once the child's expected returns are controlled for.

1.5 Effect of a Randomized Information Intervention on Subjective Expectations

Half of the households in wave 8 that were eligible for this module were provided information about the average annual earnings for men and women aged 26-34 who are working full time with, and without, a degree, and their respective employment rate.[12] Households received the information sheet presented in Appendix A2 just after their wave 8 interview, and by post again about 6 months prior to their wave 9 interview.

Table 10 shows that the treatment and control groups are balanced on baseline expectations and on most demographic characteristics. However, households in the treatment group are 15% more likely to have at least one parent with a University Degree than the control group at baseline. Our analytical sample for this section includes respondents who were interviewed at both waves 8 and 9. This resulting sample is very similar to the baseline sample in terms of characteristics. Again, it is balanced on expectations and most characteristics by treatment group, except for household degree. We discuss this at the end of section 5.2.

[12] The treatment assignment was implemented prior to wave 8 by using a random number generator and a cut-off at the household level whereby households above (below) a certain number were assigned to the treatment (control) group. Stratified sampling was not used.

Table 10 Balance Tables. Report the Wave 8 mean of the treatment and control groups by the subjective expectations questions at the individual level using our wave 8 (columns a - b) and wave 9 (columns c-f) samples. Columns c – d show the mean responses for the parents who we do not observe in wave 9. Columns e – f show the parents are interviewed for our module in wave 9

	(a)	(b)	(c)	(d)	(e)	(f)
By Observable Characteristics at the Household Level:	Interviewed in Wave 8		Not Interviewed in Wave 9		Interviewed in Wave 9	
	Control	Treatment	Control	Treatment	Control	Treatment
Child Over 15	.45	.52	.44	.48	.46	.57
Parent Over 45	.51	.46	.54*	.38	.54	.57
Child Male	.51	.54	.44	.49	.54	.56
Parent Male	.34	.31	.34	.26	.38	.44
HH Degree	.46**	.61	.48	.55	.48***	.70
High SES	.49	.51	.42	.48	.55	.60
Parent Married+	.59	.59	.56	.52	.66	.73
White British	.76	.68	.64	.65	.80	.70
Ethnic Other	.10	.12	.20	.22	.06	.13
England	.93*	.85	.16	.13	.94	.89
One Parent Respondent	.59	.54	.94**	.82	.52	.44
Max n (households)	104	121	39	58	65	63
Variable at the individual Level:						
Chance of Applying to University	77.6	76.4	77.1	69.3	77.9	81.3
Chance of Applying With Scholarship	82.0	82.8	79.6	78.2	83.0	85.9
Chance Finish University	90.4	89.0	90.1	87.5	90.5	90.0
Expected Earnings at 30 With Degree	32.5**	35.3	30.0	33.0	33.5*	37.0
Expected Earnings at 30 No Degree	24.1	24.4	22.0	22.8	25.3	25.7
Expected Earnings at 30 With Degree Population	32.4	31.7	33.6	31.7	31.8	31.7
Expected Earnings at 30 No Degree Population	21.8	22.4	21.2	21.8	22.1	22.8
Expected Returns to a Degree at 30 Population	10.3	9.6	12.3	10.4	9.3	9.0
Expected Returns to a Degree 30	8.8	10.6	9.0	10.1	8.8	11.0
Chance Employed With Degree	90.3	92.3	89.3	91.6	90.8	92.7
Chance Employed With No Degree	89.1	85.0	86.2	83.8	90.5*	86.0
Max n (Individual)	147	177	50	77	97	100

Stars indicate significance as the following labels * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

+The national average was 68% in 2017 (ONS). This suggests that parents in our sample in wave 8 are less likely to be married than in the population.

We investigate the effect of the information intervention on respondents' accuracy and subjective expectations by estimating the following ANCOVA specification:

$$Y_{i,t+1} = \alpha T_i + \gamma Y_{i,t} + \beta X_i + \epsilon_i$$

Where $Y_{i,t+1}$ is individual i's wave 9 outcome, T_i is a treatment dummy equal to one if individual *i* received the treatment and zero otherwise, $Y_{i,t}$ is i's outcome at wave 8, X_i are demographic characteristics. Note that our standard errors are clustered at the household level, which is the level of the randomization.

1.5.1 Treatment Effect on Parents Expected Earnings Accuracy

By providing information on population earnings, the treatment may have improved respondents' accuracy in that regard. We therefore start by investigating its impact on the accuracy of parent's beliefs about the average earnings at 30. Figure 2 shows that the distribution of error in population earnings for the treatment group has its mode closer to zero compared to the distribution of the control group for the earnings with a degree (left panel) but there is no large difference for the earnings without a degree (right panel). Parent's beliefs about population earnings with a degree at 30 who received the information are 15% more likely to be within 10% of the True Value and the fourth column shows that they are 14% more likely to be within £3k of the True Value (both significant at the 1% level, not shown). Similarly, Table 11 shows that the treatment reduces parental error by £1.5k in absolute terms (column 2). This evidence shows that the provision of information reduces the mean error in beliefs about population earnings with a degree. It is worthwhile to note that we only observe treatment effect on the accuracy of population earnings with a degree, even though there is substantial error at baseline about population earnings with no degree.

Table 11 OLS Treatment on Wave 9 Errors (actual earnings – beliefs) in parents beliefs

	(1)	(2)	(3)	(4)
	Error in Parents Beliefs about Population earnings			
	With Degree		No Degree	
		Absolute Value		Absolute Value
Treatment	-1809.1	-1518.2**	193.4	-400.3
	(1131.5)	(741.6)	(739.6)	(532.1)
Wave 8 Errors	0.175*	0.158*	0.227**	0.336***
	(1.93)	(0.0850)	(0.0991)	(0.0705)
Child Over 15	1879.8	1676.2*	442.8	-440.2
	(1397.7)	(926.6)	(909.6)	(605.8)
Parents Over 45	-158.3	-1046.6	-410.6	-970.1
	(1364.7)	(850.6)	(980.8)	(619.9)
Male Child	3705.5***	3365.8***	2375.0***	757.7
	(1259.7)	(764.4)	(785.2)	(530.1)
Male Parent	-952.5	-482.1	-1851.8***	-908.2**
	(861.8)	(733.3)	(623.9)	(406.4)
HH Degree	1025.5	438.3	-616.4	-739.1
	(1512.7)	(1005.1)	(874.4)	(639.0)
HH High Income	-687.3	-7.857	-102.0	500.8
	(1237.0)	(808.8)	(921.7)	(578.4)
Married	-2079.2	-1713.2	-1226.4	-519.4
	(1638.5)	(1063.1)	(1041.9)	(711.5)
White British	248.8	341.5	291.4	-1044.1
	(1491.6)	(1079.2)	(1195.4)	(740.6)
Ethnic Other	-770.5	142.2	1917.2	-770.4
	(2158.8)	(1544.5)	(1450.7)	(948.3)
England	-2474.3	-2122.5**	-3762.2***	-1915.4*
	(1597.5)	(990.2)	(1301.0)	(989.3)
Constant	5775.0**	8368.6***	6127.7***	7229.3***
	(2598.9)	(1614.2)	(1907.2)	(1336.5)
R2	0.146	0.164	0.227	0.264
DV mean	5440	7871	3053	5016
N	235	235	232	232

The standard errors are reported in parentheses and the stars indicate statistical significant to our usual levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

1.5.2 Treatment Effect on Parents Expectations

We next explore how parents update their beliefs and expectations in response to the information we provided. Table 12 reports the coefficient associated with the dummy Treatment on parental expectations. Row (a) shows the results for all parents. We find that the information treatment increase expectations about population returns by £2.4k (statistically significant at the 5% level). The effect is similar for mothers (row b) and fathers (row c), although slightly less precisely estimated for fathers (p-value=0.13). This increase in perceived population return is not accompanied by an increase in the returns to a degree for their own child. In rows (a) to (c), the coefficients associated with the treatment dummy are positive but much smaller in the specification for child's return compared to population returns, and the standard errors are very large. Although our sample is relatively small, this suggests that expected returns about own child, for whom parents may have quite a lot of private information, is less responsive to general information about the labour market than beliefs about population return.

Our intervention also included information about employment rate. Row (a) shows no effect on the subjective probabilities of employment when we look at all parents, but we see an 8 percentage point increase in the probability of employment with a degree for mothers (statically significant at 10%), and a 7 percentage point decrease for fathers (statistically significant at 5%). Perhaps not surprisingly given that there is no change in the expected returns to a degree for their child, there is no statistically significant treatment effect on the expectations to apply to university or the chance to have a degree at age 30.

Despite the relatively small sample size, rows d-g investigates the heterogeneity in treatment effect using interactions by: (i) child's gender, (ii) SES, (iii) household degree, (iv) baseline accuracy. Overall, there does not seem to heterogenous treatment effects according to these categories.

Recall that our treatment group is more educated than the control group. While we control for household degree in all our specification, our results are robust to using regression adjustment as in Cattaneo (2010) and propensity score matching, on baseline beliefs and observable characteristics (not reported but available on request).[13] The treatment effects on population returns to a degree are of similar magnitude as in the OLS specification, and precisely estimated. There is also a large (6 percentage point) and precisely estimated treatment effect on the probability to apply to university when using propensity score matching. But this result does not hold in the regression adjustment, and therefore seems sensitive to the underlying assumptions. For propensity score matching, similarity between subjects is based on estimated treatment probabilities, while for the regression adjustment it is based on a weighted function of the covariates for each observation.

1.5.3 Treatment Effect on Children's Expectations

We only have 73 young people who participated both in waves 8 and 9. We still estimate the treatment effect for children (now reported). While none of the coefficients associated with treatments are statistically significant, the magnitude of the effects on own versus population earnings are different than what we have observed for parents. The coefficient associated with treatment is £2.8k for own earnings returns, compared to £0.5k for population returns. It is plausible than young people have more malleable expectations about their own labour market outcomes than their parents.

[13] Using a matching strategy we create a potential outcome for each respondent by comparing all the respondents in the treatment (control) group with a respondent who looks most similar to them in the control (treatment) group. We then and take the average of the difference between the observed and potential outcome for each respondent.

Table 12 Treatment effects on parental beliefs.

	Change Degree by 30	Pr Apply to University	Pr Apply to University With Scholarship	Returns to a degree at 30 Population	Returns to a degree at 30 Own Child	Employment Returns to a Degree	Pr of Employment With a Degree	Pr of Employment Without a Degree	Expected Tuition
	Subsample analysis by observable characteristics								
(a) All Parents	-0.805	1.958	1.781	2350.5**	875.2	-2.246	2.505	5.206	1205.2
	(3.236)	(3.928)	(3.998)	(1081.4)	(1685.1)	(3.067)	(2.980)	(3.203)	(875.6)
(b) Mothers	0.999	2.490	3.044	2627.9*	425.5	0.270	7.957*	7.048	812.2
	(4.484)	(5.868)	(6.123)	(1459.4)	(2416.4)	(3.664)	(4.571)	(4.267)	(824.2)
(c) Fathers	-1.925	2.103	2.431	2456.6	1327.2	-8.930	-6.759**	2.489	2855.6
	(4.588)	(5.982)	(4.876)	(1620.4)	(2694.9)	(5.680)	(3.168)	(4.236)	(2205.0)
	Interactions Using All Parents								
Treatment x:									
(d) Male Child	-3.017	-1.283	-2.619	-761.7	1115.4	-7.849	-12.52**	-2.212	757.5
	(5.995)	(7.112)	(7.354)	(1930.3)	(3141.6)	(5.614)	(5.248)	(5.389)	(1548.5)
(e) High SES	7.094	-9.456	-4.216	45.98	5186.9	2.615	0.138	0.580	-1792.4
	(7.097)	(8.383)	(9.241)	(2205.7)	(3270.9)	(5.598)	(5.803)	(6.265)	(1705.5)
(f) HH Degree	5.649	-7.894	2.111	-1833.4	65.26	8.511	-1.858	-7.224	-1415.3
	(7.547)	(8.258)	(9.533)	(2185.0)	(3372.3)	(5.678)	(6.477)	(6.364)	(1825.2)
(g) Wave 8 Accurate (within 10%)	-12.67	0.561	5.949	1938.2	-11569.9*	8.000	-6.857	-3.058	-3600.2
	(19.89)	(14.07)	(11.37)	(2884.6)	(6864.9)	(8.095)	(8.786)	(10.17)	(3519.2)
N	183	134	131	229	138	126	151	159	119

SE in parentheses, starts indicate significance as the following labels * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Rows d-g report the interaction by the treatment and observable characteristics.

1.6 Conclusion

Increasing social mobility is high on the government agenda in the UK, and many other countries. Widening participation into Higher Education is one possible pathway but, despite recent effort, there is still a large gap participation between high and low SES. We investigate whether differences in knowledge about the labour market returns to a degree might be responsible for this gap. Our focus on the perceived labour market returns to a degree stem from the fact that they ought to be an important driver of the decision to go to university. Indeed, in our data, parents/young people who expect higher labour market returns from a degree also expect a higher probability that their child/they will apply to university.

Our detailed subjective expectations data reveal two important facts. Parents and young people from various SES backgrounds hold similar beliefs about the earnings return and employment returns to a degree. Moreover, parents under-estimate on average the population earnings return to a degree. It is therefore unlikely that the information gap about the labour market advantage of a degree explains the SES gap in participation. But providing information on earnings may help all families to make better informed-decision, irrespective of SES background.

We have also found that a very light-touch information intervention, such as showing some statistics about population earnings and employment to families, is powerful enough to change parents' expectations about population earnings so that they become more accurate, with changes still visible 6 months later. This information also increased participants' perceptions about the returns to a degree in the population. However, this intervention did not change parents' perceptions about the future labour market outcomes of their own children. Possibly due to private information, those may be less responsive to information about population statistics.

We also provide indirect evidence that financial constraints at the time of university application are not a major factor in the decision to apply as differences in application expectations persist by family background even in the hypothetical situation of being provided a scholarship that would cover all costs. This does not mean that financial constraints are irrelevant; rather that they may matter earlier on - by affecting primary and secondary school quality, for example, or access to tutoring.

More research is needed to better understand the underlying mechanism explaining the gap in higher education application by socio-economic status. Psychological costs are found to be important for educational choices (Eisenhauer et al., 2015) and those may be different for individuals who come from different backgrounds. Information gaps might still be relevant in other domains than labour market returns to a degree, such as the non-pecuniary returns to a degree (Belfield et al., 2020, Boneva and Rauh 2017).

1.7 Figures

Figure 1 Parents Accuracy about the returns to a degree (actual returns – belief) we define error by subtracting their beliefs from the 'True Value', a positive (negative) error stipulates that the respondent underestimates (overestimates) population earnings.

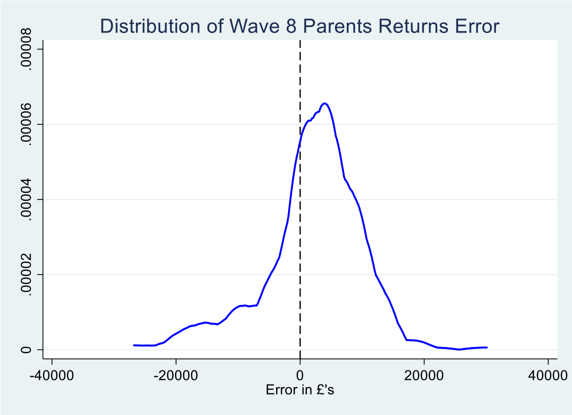


Figure 2 Parents Wave 9 Accuracy about the returns to a degree (actual returns – belief) we define error by subtracting their beliefs from the 'True Value', a positive (negative) error stipulates that the respondent underestimates (overestimates) population earnings.

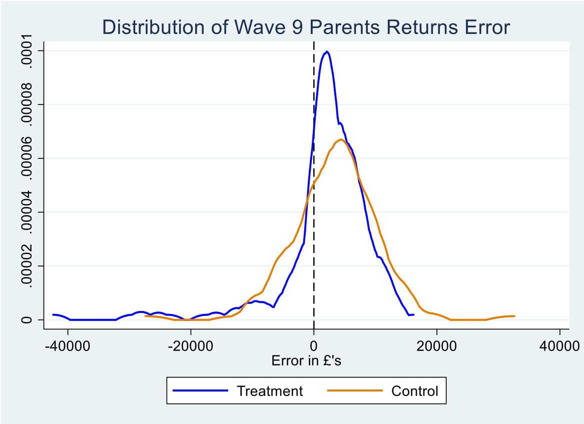


Figure 3 Parents Application intentions without a scholarship Wave 8 (LHS) and Wave 9 (RHS) by Treatment

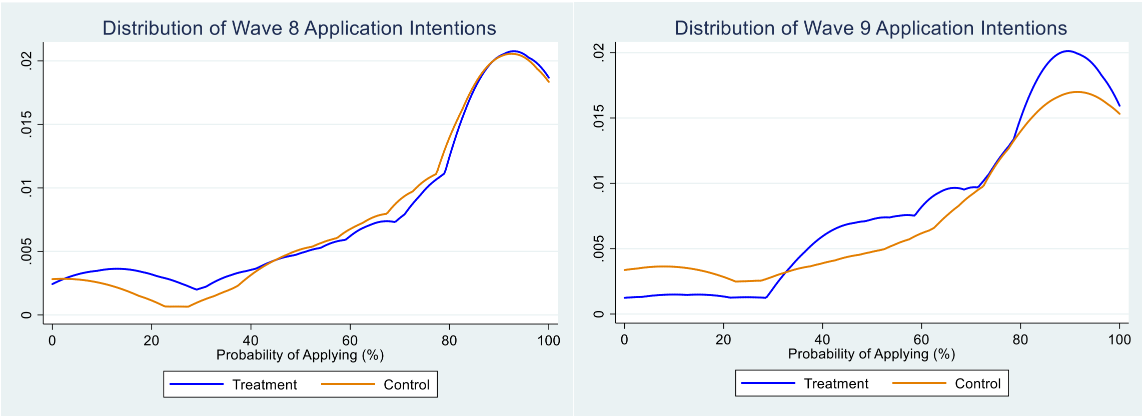
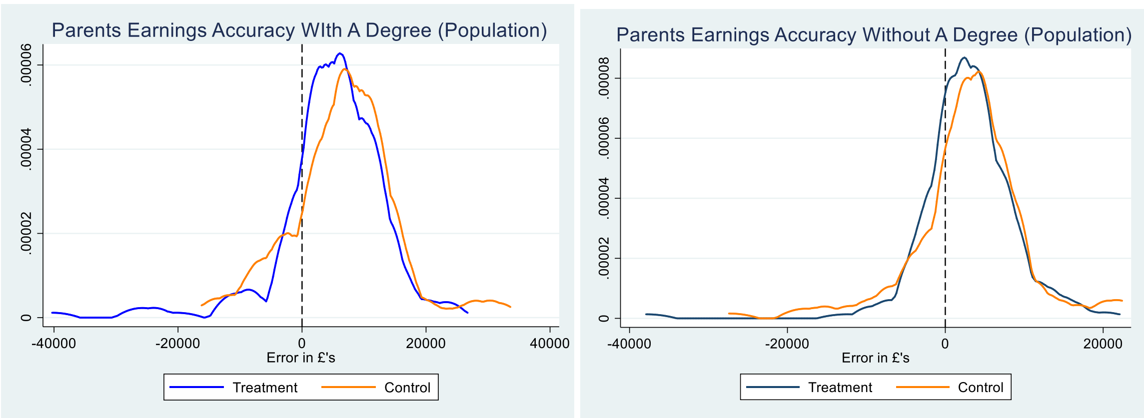


Figure 4 Parents Accuracy of Population earnings rescaled (actual earnings – belief) with (LHS) and without a degree (RHS) at 30.



Chapter 2

Bad Economy, Good Teachers? The countercyclicality of enrolment into Initial Teacher Training Programmes in the UK

2.1 Introduction

Shifts in labour demand caused by technological growth and an increase in trade with developing counties have resulted in human capital playing a more prominent role in securing a well-paid position in the labour market (David and Dorn 2013, Goos et al., 2014, Michaels et al., 2014). This is the case in England where recent evidence shows that the decision to apply to university is motivated by expected labour market returns (Delavande et al., 2018). However, the lag between the decision to apply to university and graduation means that the investment in human capital might not pay off if entry into the labour market occurs during a period of low labour demand. Research shows that graduating during a period of low labour demand can have scarring effects on labour market outcomes (Altonji et al., 2016, Cockx and Ghirelli 2016, Kahn 2010, Oreopoulos et al., 2012) . Indeed, young people who graduate during a recession are less likely to find a job and those who do face a wage penalty (Baert et al., 2013, Del Bono and Morando 2016, Oyer 2006, Shvartsman 2018, van den Berge and Brouwers 2017).

To avoid the negative effects of entering the labour market during a recession individuals may decide to defer entry by remaining in education. Existing evidence shows that economic conditions do effect education related choices in a variety of settings including the decision for graduates to enrol into postgraduate study and the decision for school leavers to enrol into post-compulsory schooling (Barr and Turner 2015, Clark 2011, Del Bono and Morando 2016, Foote and Grosz 2020, Kondo 2015). In this paper, we test the hypothesis that a possible response to periods of low labour demand is for graduates to go into teaching, a profession that generally requires at least one year of postgraduate study, and an occupation whose demand is mostly unrelated to economic conditions as it depends on population demographics and government policies. Specifically, we exploit the plausibly exogenous variation in labour market conditions at the time of graduation to investigate how this affects the probability that a graduate will enrol onto an Initial Teacher Training Programme (TTP). We find no evidence that graduating during a period of high unemployment has any effect on the probability that a graduate will enrol onto a TTP. While the quantity of graduates who enrol in TTP's might not necessarily respond to labour market conditions due to capacity constraints, the composition of trainee teachers might still be affected. Our heterogeneity analysis suggests a compositional effect on the diversity of trainee teachers - more male graduates, more graduates from ethnic minority backgrounds and more Russell Group graduates as well as a positive effect on subject specific shortages (more Physics graduates).

Understanding the factors affecting the supply of teachers is important because teachers are an essential component of the education production function whose impact on the development of human capital impacts student outcomes in both the short (Hanushek et al., 2014) and the long run (Chetty et al., 2011). The magnitude of the effect is illustrated by Hanushek (2011a) who shows that a teacher who is 0.25sd more effective at raising student test scores than the average teacher annually generates marginal gains of more than $105,000 for a class of twenty students. Furthermore, teachers have a significant impact on the wider economy as emphasised by Hanushek and Woessmann (2011), who show that improving test scores by 0.25sd (just over half the difference between the US and Canada) would increase the present value of GDP by $44 trillion.

In the simplest terms, the demand for teachers is driven by the quantity of school aged children and the policymakers' desired pupil to teacher ratio (Zabalza et al., 1979). Even though we can reject the notion that class sizes have an economically meaningful impact on pupil performance as long as policymakers prioritise small class sizes, growing pupil numbers will ensure that teacher demand is unlikely to fall (Woessmann and West 2002).

The supply of teachers comes down to the retention of current teachers, the return of qualified teachers who are not teaching and the recruitment of graduates into teacher training programmes (Chevalier et al., 2007). The recruitment of graduates to teacher training programmes will be our focus here as it is the largest source for filling new demand needs. In England, teacher training occurs after at least three years of undergraduate study and students typically apply to these programmes during the final year of their undergraduate course. Similar to a bachelor's courses, teacher training requires fees to be repaid through income contingent loans (see section 2.1).

Existing research provides evidence that the supply of teachers is sensitive to labour market conditions in England. Using graduate cohort data from the 1960s to the 1980s and the 1960s to the 1990s Dolton and Mavromaras (1994) and Chevalier, et al. (2007), respectively found that the graduate unemployment rate and relative wages have a significant impact on the probability that graduates will go into teaching. However, the graduates in their data are observed between five and seven years after graduation. Therefore, it is difficult to distinguish between enrolment and retention, as it is possible that graduates who are successfully placed onto a teacher training programme are less likely to leave the profession during periods of low labour demand.[14]

[14] Attrition rates in England are very high, roughly one in three new teachers quit within five years.

While there is evidence that the graduates decision to go into teaching is countercyclical this does not, necessarily, mean that periods of low economic activity translate into lower pupil-to-teacher-ratios. This is because teachers are costly - they are the largest component of educational expenditure - and school funding is not, necessarily, immune to periods of low economic activity. Therefore an increase in the supply of teachers will only lower the pupil-to-teacher-ratio if the system have both the capacity and the funds to absorb them. In England, for instance, many aspects of school funding is ‘ring fenced’ which means current, and planned, expenditure on salaries is generally protected. As a consequence, even in a recession, schools generally will have the funding to maintain its current workforce and fill existing vacancies and temporary filled posts. As a consequence pupil-to-teacher-ratios in England tend to be more related to government policies than economic conditions, measured by the GDP growth rate (Dolton et al., 2003). But this is not the case in every context. In America, for example, many schools faced severe budgetary issues due to the 2008 financial crisis causing almost 300,000 teachers to lose their jobs. As a consequence pupil-to-teacher ratios to increase to 17.4, the highest level since 1989/90 (Evans et al., 2019).

This paper contributes to this literature in three ways. First, we are able to more precisely estimate the effect of labour market conditions on teacher supply as we observe graduates six months after graduation rather than five to seven years after graduation. Second we test the hypothesis in a new environment, one with tuition fees and a formal assessment. The existing evidence from England uses data prior to the introduction of tuition fees, when there were no financial costs associated with teacher training, or certification requirements, i.e. applicants did not have to pass a formal assessment (Dolton and Klaauw 1995, Dolton and van der Klaauw 1996, Dolton and Mavromaras 1994). These are two important distinctions as empirical evidence demonstrates that these policies both have a meaningful impact on the supply of teachers. Castro-Zarzur et al., (2019) finds that tuition fees make teaching less attractive and negatively impacts the quality and quantity of students who go into teaching. A relatively small body of literature, including Hanushek, et al. (1995) and Manski (1987), shows that teaching certification requirements reduces supply. Therefore, we would expect the introduction of tutition fees, and certification requirements to change the relationship between economic conditions and enrolment onto a TTP – particularly for male graduates who tend to be more responsive to costs incurred.

Our third contribution is to investigate if the effect that graduating in a tough labour market has on the composition of graduates entering teaching measured by their university attainment (degree classification), the prestige of the university they attended and degree studied as well as their gender, ethnicity and socioeconomic status. Existing evidence suggests that salaries and economic conditions affect the composition of individuals who enter the profession. In the UK, Nickell and Quintini (2002) show that the decline in teachers' relative wages caused the quality of men going into teaching, as measured by childhood test scores, to fall. Using administrative data on teachers in Florida, Nagler et al., (2015) found that teachers who started their career during a recession were more efficient in raising student test scores. However, this relationship is not well-established. Hanushek et al., (1999) and Hanushek and Rivkin (2007) using a rich data set on public schools in Texas, show that salaries do not explain teacher quality or ability, while Horvath et al., (2018) found that other factors are stronger predictors of entry into teaching – the most prominent of which is how much individuals enjoyed their teaching experiences during their teacher training.

Teaching is a female dominated profession across the OECD. A potential reason why the majority of teachers tend to be female is that, consistent with the gender pay gap, women are significantly less likely to face a wage penalty in teaching compared to their male counterparts (Fullard 2019b). Moreover, the difference in the relative attractiveness of teaching in terms of earnings might also explain why schools struggle to recruit and retain graduates with a degree in a STEM subject (Clotfelter et al., 2008).[15]

Our ability to investigate the effects of economic conditions at graduation by observable charactersitcs is important as existing research suggests that a teacher’s ethnicity and sex influence pupil performance. Dee (2007) found that same sex teachers in high school generally have a positive effect on pupil performance, while Hermann (2017) found that female teachers had a strong negative effect on high-achieving boys in England. Gershenson et al., (2018) found that black pupils assigned to black teachers in the Tennessee STAR experiment were significantly more likely to graduate from high school and enrol into college

Our data, the Destination of Leavers from Higher Education survey (DLHE), is collected 6 months after graduation on the population of graduates from all UK Higher Education Institutions. Due to data availability we focus our analysis on the graduation years from 2002/03 to 2011/12. The data contains information about each graduate’s labour market outcomes, prior education (vocational and academic qualifications, and performance levels obtained both before and during university), family background, and demographic characteristics. We combine this graduate level data with labour market statistics and the Index of Multiple Deprivation (IMD) produced by the Office for National Statistics (ONS), data on teacher vacancies from the Department for Education’s (DfE) School Workforce Census (SWC) and a measure of economic conditions from the Labour Force Survey (LFS). Due to the size and quality of our data, we can estimate the effect that economic conditions have on the enrolment behaviour of graduates onto TTPs and investigate the effects on the composition of trainees. As economic conditions are plausibly exogenous – young people in our setting enrol onto a specific degree programme with a fixed graduation date, typically

[15] Note STEM is an acronym that stands for science, technology, engineering and mathematics.

three years after enrolment, and there is very little scope for deferring graduation or switching programmes - these estimates are intended to be interpreted as causal effects.

This paper is organized as follows, section 2 discusses the institutional setting, sections 3 discusses the empirical strategy , section 4 discusses the data we use, section 5 presents our descriptive statistics, section 6 presents our main results, section 7 our robustness checks and we conclude in section 8.

2.2 Higher Education in England

In this paper, we restrict our analysis to the English-domiciled students graduating from English Universities, as Scotland, Wales and Northern Ireland have some differences in their teacher training requirements and education systems. In England, all teachers in state schools are required to have a minimum of a lower second class (2:2) degree, qualified teacher status (QTS), and relevant school experience. To obtain a 2:2 degree, a student must enrol at a university and achieve an overall mark of between 50-59%. For an English student to enrol at a UK university, they must apply through the Universities and Colleges Admissions Service (UCAS). Students typically apply in the second year of their A-Levels (See Appendix for further details of the application process in England).[16]

Unlike many countries, including the US, students in England enrol onto a specific programme at university and there is little switching between degree subjects and institutions, and a low dropout rate (Vignoles and Powdthavee 2009). Consequently, there is little scope for undergraduates to defer their graduation, dropout or switching degrees in response to periods of high unemployment. As the degree subject is chosen prior to university enrolment and it is not practically possible for graduates to adjust either their degree subject or when

[16]A-levels are Key Stage 5 in the national curriculum. Students typically start their first year at 16 and finish at 18. KS5 typically occurs at a sixth form college.

they graduate in our setting, we argue that the subject specific unemployment rate, at time of graduation, is exogenous.

2.2.1 Initial Teacher Training Programme

During the final year of undergraduate studies (typically a student's third year), students can apply through UCAS to do a Post Graduate Certificate in Education (PGCE), which is a one year Initial Teacher Training Programme (TTP) – a TTP is any teacher training programme that leads to qualified teacher status (QTS). This programme is made up of taught classes and school placements. Like the undergraduate process, students apply to five institutions/programmes through UCAS, attend interviews and are either accepted or rejected. If a student is rejected from all five of their choices, they have a second round, named 'Apply 2'. In this round, students apply to one institution/programme at a time, but can make an unlimited number of choices until they are accepted onto a programme. According to UCAS's Analysis and Insights data, over 2,500 people (around 11% of those enrolled onto TTPs) found a teacher training place through Apply 2 in 2016. After completing a PGCE students are recommended for QTS which is the requirement to teach in England.

In our data, we observe if a graduate is enrolled onto a teacher training programme six months after graduation, but we do not observe which programme they are enrolled on. The most popular route to QTS is the PGCE but there are other routes.[17] These include Schools Direct and Postgraduate Teaching Apprenticeships. Like a PGCE, these are one-year routes also applied for through UCAS. But, unlike a PGCE, they are salaried programmes where schools, in conjunction with partnering schools or a university, train teachers on the job. There are two similar employment-based teacher training programmes, Teach First and

[17] The Initial teacher training census 2014-15 shows that 72% of those enrolled were on a PGCE. To this day, the PGCE remains the most popular route, but the alternative options have become more popular. For example, in 2009, 485 graduates enrolled onto Teach First, while in 2017, 1,300 were enrolled.

Premier Pathways, where students work for two years and are awarded a PGCE upon completion. A final route into teaching is a three year undergraduate degree in Education. But not all undergraduate degrees in education lead to QTS, and for those that do not, to achieve QTS, students would have to take one of the programmes outlined above (See the appendix for further details about initial teacher training programmes).

2.2.2 Testing Requirements

To enrol onto a TTP, all students are required to pass the professional skills test. This test assesses the numeracy and literacy of potential teachers. Since 2012, the pass threshold was increased (students had to achieve a higher score to pass) and students were limited to 2 resits. Students who fail their two resits are not allowed to retake the test for 24 months. Due to of these changes the Department for Education professional skills tests statistics show that the pass rate fell from 98% (99%) in numeracy (literacy) in 2011/12 to 85% (87%) in 2012/13.

2.2.3 Tuition Fees

From 1962, full time undergraduate students in the UK did not have to pay any tuition fees until their reintroduction in 1998 by the Teaching and Higher Education Act. Fees were initially capped at £1,000 per year for the cohort starting a university course in 1998. These tuition fees also apply to anyone starting a PGCE. The 2004 Higher Education Act tripled fees to £3,000 per year for the cohort starting in 2006. Following the Browne review, the UK Parliament capped fees at £9,000 for the 2012 cohort. Institutions typically set tuition fees to the highest possible level, but there is some variation. Table 1 in the Appendix presents the fees schedule by year of entry.

2.3 Empirical Strategy

The aim of this paper is to investigate if labour market conditions have an effect on graduates' decision to enrol onto a teacher training programme (TTP). To do this, we are going to exploit the variation in the unemployment rate at the time of graduation, which we assume is exogenous as we know students in England cannot choose their time of graduation once enrolled.

Our unit of analysis is a graduate i who obtained a degree in the field of study f, from Higher Education Institute h, lives in region d and is observed at time t(six months after graduation). Our principal interest is to establish if the unemployment rate during the previous year, $U_{f,t-1}$, affects the probability that they will be enrolled onto a TTP (Y_{ifhdt}). Our initial specification is the following:

$$\mathrm{Y_{ifhdt}} = \beta_0 + \beta_1 \mathrm{U_{f,t-1}} + \theta'_{\mathrm{t}} + \sigma_d + \mu_h + \delta_{\mathrm{f}} + \epsilon_{\mathrm{ifhdt}} \tag{1}$$

Where $\beta_1$is our coefficient of interest which denotes the effect of a one percentage point increase in the subject specific unemployment rate on the probability that a graduate is observed in a TTP six months after graduation. Note that the unemployment rate that each graduate is assigned is the average of the unemployment rate the two quarters before, and two quarters after June, which is when the student graduates. We also include year fixed effects (θ'_{t}), region fixed effects (σ_d), institution fixed effects (μ_h) and field of study fixed effects (δ_{f}). Our robust standard errors are clustered at the year subject level.

Our main specification uses the subject specific unemployment rate. As we always include subject fixed effects, we are exploiting within subject across time variation. However, we might be concerned that the composition of each cohort differs. Therefore, we also control for graduates' observable characteristics, including socioeconomic status (SES) and academic characteristics (X_{ifhdt}), as well as sex, ethnicity and degree classification.

There is evidence that both the decision to enter university and the degree a student studies is responsive to the labour market conditions at time of enrolment. We therefore include regional unemployment rates, measured by the claimant count, the year before entry into university ($U_{d,t-4}$) to control for this. In addition a graduate's decision to enrol onto a TTP might be sensitive to the fluctuation in the demand for teachers at the regional level. We use a novel approach to control for this by using teacher vacancies at the regional level during the year of graduation ($V_{d,t-1}$).

Finally we include subject specific time trends to account for any systematic changes in enrolment onto TTP over time by field of study ($\gamma(\delta_f * t)$). Therefore our main specification is:

$$Y_{ifhdt} = \beta_0 + \beta_1 U_{f,t-1} + \beta_2 X_{ifhdt} + \beta_3 V_{d,t-1} + \beta_4 U_{d,t-4} + \theta'_t + \sigma_d + \mu_h + \delta_f + \gamma(\delta_f * t) + \epsilon_{ifhdt} \qquad (2)$$

Our identification strategy takes advantage of the fact that students in England enrol onto a specific undergraduate programme at the age of 18, and there is very little scope for them to change programmes/institutions and dropout rates are low. As the time of graduation, and field of study, is largely fixed, students are unable to react to changes in labour market conditions. Therefore, we argue that the subject specific unemployment rate, at the time of graduation, is plausibly exogenous and $\beta_1$represents the causal effect of labour market conditions on enrolment onto a TTP.

We will also consider the interaction of $U_{f,t-1}$ with dummies including the graduate's sex (male), ethnicity (white), degree classification (2:1 or above), university prestige (Russell

Group) and socioeconomic status to investigate how periods of high graduate unemployment might affect the composition of graduates enrolled onto TTPs.

We will also use subsample analysis to investigate how the effect differs by degree subject. We will do this by restricting our sample to graduates with a specific degree subject and run a modified version of equation 2 by dropping our year fixed effects, subject fixed effects and subject specific time trends:[18]

$$\mathrm{Y_{ihdt}} = \beta_0 + \beta_1 \mathrm{U_{t-1}} + \beta_2 \mathrm{X_{ihdt}} + \beta_3 \mathrm{V_{d,t-1}} + \beta_4 \mathrm{U_{d,t-4}} + \sigma_d + \mu_h + t + \epsilon_{\mathrm{ihdt}} \qquad (3)$$

Using the subject specific unemployment rate relies on assumptions about graduate mobility. Although graduates are highly mobile in England, a region specific graduate unemployment rate $\mathrm{U_{d,t-1}}$ might be more appropriate. Therefore, we modify equation 2) by replacing subject fixed effects and subject-specific trends with regional fixed effects and region-specific trends $(\delta_d * t)$:

$$\mathrm{Y_{ifhdt}} = \beta_0 + \beta_1 \mathrm{U_{d,t-1}} + \beta_2 \mathrm{X_{ifhdt}} + \beta_3 \mathrm{V_{d,t-1}} + \beta_4 \mathrm{U_{d,t-4}} + \theta'_t + \sigma_d + \mu_h + \delta_f + \gamma(\delta_d * t) + \epsilon_{\mathrm{ifhdt}} \qquad (4)$$

Here, the standard errors are clustered at the year-region level and the region of analysis (d) is either the home domicile or the region of university, depending on whether we are using the university or the home domicile unemployment rate.

The unemployment rate might be correlated with other factors that might influence the decision to go into teaching. Therefore, we will also estimate the effect of teachers relative wages, at the regional level, on the probability of enrolling onto a TTP by estimating equation

[18] Note that our standard errors for this specification, where we restrict our sample to graduates with a specific degree (equation 3) are clustered at the year level to take into account possible correlation between graduates over time. To adjust for the relatively small number of clusters, we implement the wild cluster bootstrap procedure as recommended by Cameron and Miller (2015). To implement this in stata we use the boottest command using 1,000 reps (Roodman et al., 2019).

4 but replacing $U_{d,t-1}$with $Wage_{d,t-1}$, which is the difference in the natural log of teacher and non-teacher wages:

$$Y_{ifhdt} = \beta_0 + \beta_1 Wage_{d,t-1} + \beta_2 X_{ifhdt} + \beta_3 V_{d,t-1} + \beta_4 U_{d,t-4} + \theta'_t + \sigma_d + \mu_h + \delta_f + \gamma(\delta_d * t) + \epsilon_{ifhdt} \quad (5)$$

Where β_1,our coefficient of interest, denotes the effect of a one percentage point increase in teachers relative wages.

2.4 Data

The dataset we use in this paper comes from the Destination of Leavers from Higher Education (DLHE). The DLHE is a survey that is carried out on the whole population of graduates from all UK Higher Education Institutions six months after graduation. The survey is carried out by the Higher Education Statistics Agency (HESA) and the data is linked to data from the Universities and Colleges Admissions Service (UCAS). The graduation years we use are from 2002/03 to 2011/12.[19]

We remove all the respondents who graduated in veterinary sciences as: i) none of our respondents with a veterinary degree enrolled onto teacher training programmes, and ii) we do not have any variation in the unemployment rate at the time of graduation to exploit. We also drop graduates from the following subjects, as we do not have significant variation in TTP enrolment over time: Medicine, Agriculture, Architecture, Engineering, Law, Business and Communication.[20] This leaves us with a sample of 741,815 graduates from 10 subjects.

Most of these graduates are female (58%), white (86%) and state school educated (86%). In terms of academic achievement 95% achieved at least a 2:2 which is the minimum

[19] DLHE has a non-response rate of about 19% so our data represents a sample of labour market outcomes for roughly 81% of all university graduates from 2002/02 to 2011/12.
[20] We drop those who study Medicine, Agriculture, Architecture, Engineering, Law, Business and Communication as only 16, 4, 2, 21, 16, 56 and 10 individual graduates go into TTPs respectively.

requirement to teach. Specifically, 14% of the graduates achieved a 1st class degree, 54% achieved a 2:1 and 27% achieved a 2:2. This is largely similar to the distribution of achievement in the whole population such that we are confident of the external validity of our results.[21]

Most of our graduates obtained a degree in Arts (20%), Biological Sciences (17%), Social Studies (15%), Languages (12%), History and Philosophy (10%) and Physical Sciences (8%). The sample characteristics are presented in Table 1.

2.4.1 Unemployment Rate by Field of Study

We use the 2003-2012 Labour Force Survey (LFS) to calculate the unemployment rate by field of study at the year of graduation (U, t-1). Using the LFS, we restrict our sample to the respondents who are between 21 and 65 and have a university degree. Using this sample, we compute the unemployment rate by field of study.[22] Table 2 shows that the average unemployment rate is just over 3%, peaking at 4% in 2010.

The field of study with the highest average unemployment rate is Arts (4%) and the lowest is Education (just under 1%). Social studies have the least variation in the unemployment rate over time while mathematical sciences have the largest variation (Table 2 in the appendix shows the variation in the unemployment rate by field of study).

[21] In 2012/13, for example, 19% achieved a 1st, 51% a 2:1 and 25% a 2:2 according to HESA's January 2018 Higher Education Student Statistics.

[22] We compute the unemployment rate by dividing the quantity who are unemployed by the sum of those who are employed and unemployed. We restrict our sample to those who are between 21, as that is the typical age of a university graduate, and 65, which is the retirement age. We use the retirement age and not a younger age to keep the sample size large enough to allow us to create a meaningful measure by degree subject. The number of observations we use to calculate the unemployment rate is relatively small and could bias our estimates. To minimise this we use the largest available sample (age 21-65) rather than restricting it to ages 21-30, for example.

Table 1 Descriptive Statistics of Graduates in our Sample

Variable	Frequency	Percentage (%)	Variable	Frequency	Percentage (%)
Sex			**Subject**		
Male	315,255	42.5	Biology	127,225	17.2
Female	426,560	57.5	Physics	62,265	8.4
			Maths	26,270	3.5
Ethnicity			Computer Science	55,015	7.4
White	635,850	85.7	Social Studies	111,590	15.0
Black	14,080	1.9	Languages	94,565	12.8
Asian	57,215	7.7	History/Philosophy	70,750	9.5
Other	22,370	3.0	Arts	145,120	19.6
NA	12,300	1.7	Education	43,915	5.9
			Combined	5,110	0.7
Degree Classification[+]					
1st	107,490	14.5	**Region**		
2:1	400,515	54.0	London	112,680	15.19
2:2	198,775	26.8	North East	18,815	2.54
3rd	30,755	4.15	West Midlands	67,575	9.11
Unclassified	4,270	0.6	East of England	82,065	11.06
			South East	143,725	19.37
Institution			East Midlands	61,625	8.31
Oxbridge	27,355	3.7	South West	58,040	7.82
Russell Group	181,015	24.4	Yorkshire and the Humber	64,600	8.71
			North West	77,830	10.49
			Missing	54,880	7.4

The frequencies are all rounded to the nearest 5 or 0 as required by the data providers. [+] We are missing nine respondent's degree classifications. We include them in our unclassified group. Our results do not change if we do, or do not, include them.

Table 2 Unemployment rate by graduation year (2003-2012)

Year	Mean (%)	Interquartile Range(%)$^{+}$	Range (%)$^{++}$	Std. Dev	Skewness^{+++}
2003	3.31	0.29	3.28	0.87	0.22
2004	2.61	0.87	3.26	0.85	-0.53
2005	2.57	1.40	4.51	0.92	0.39
2006	2.82	0.52	3.42	0.54	-1.89
2007	2.35	0.97	3.08	0.65	-0.90
2008	2.63	0.39	3.65	0.69	-0.62
2009	3.21	2.24	5.03	1.44	-0.42
2010	4.04	4.15	7.21	1.93	0.45
2011	3.05	0.45	5.22	0.75	-0.44
2012	3.33	2.20	3.53	1.07	-0.04
All Year	3.02	0.99	7.20	1.17	0.88

The unemployment rate is calculated using data from the Labour Force Survey. We calculate it by deviding the quantity of graduates who are unemploymed by the quantity of graduates who are employed. $^{+}$ p75-p25^{++}(min-max) $^{+++}$ Measures the degree and direction of asymmetry in a distribution, a symmetric distribution has a skewness of 0. A distribution that is skewed to the left has a negative skewness, while a distribution skewed to the right has a positive skewness.

2.4.2 Unemployment by Year of Entry

Using NOMIS, a service provided by the Office for National Statistics, we also add the regional claimant count the year prior to university enrolment to control for selection into university (U_{t-4}). For graduates whose home address is missing (7%) we use a missing dummy and assign them the national average claimant count. The claimant count is a measure of the number of people claiming unemployment related benefits. It has a mean of 2.3% a minimum of 1.2% (South East 2002 and South West 2005) and a maximum of 4.8% (North East 2000).

The argument we make here is that the claimant count at the regional level reflects the labour market that young people would have faced when they finished school. As a robustness check we also use the LFS to estimate the youth unemployment rate (aged 18-24 and without a degree) by region, where we find it has no impact on our results. We do not use a national measure as school leavers tend to be less mobile so a national measure would not be appropriate.

2.4.3 Teacher Vacancies

Graduate enrolment onto TTPs might be sensitive to the fluctuations in the demand for teachers at the regional level. But it is not clear the effect fluctuations in demand will have on the decision to teach. An increase in teacher demand could be a signal of more favourable job opportunities, but it could also be perceived as a signal of stress or burnout among teachers (high dropout rate of existing teachers) possibly deterring graduates from the profession. We use a novel approach to control for this by using teacher vacancies at the regional level. To do this we use data from the School Workforce Census (SWC) on the quantity of advertised teacher vacancies, the quantity of temporary filled vacancies (a post filled by someone who is on a contract for one term or less) and the quantity of teachers currently in posts. The SWC is a census that is completed annually by every school in England in November.[23] We create our teacher vacancies indicator by dividing the total teacher vacancies (the sum of the quantity of advertised teacher vacancies and the quantity of temporary filled vacancies) by the total quantity of teachers in current posts. We compute this measure at both the regional and national level. Specifically every graduate has a regional and national vacancy rate from the November of the year when they would have applied to teacher training ($t-1$). The highest vacancy rates are in London (2.1% in 2003), while the lowest rates are in the South West (between 0.2% and 0.4%).

2.4.4 Socioeconomic Status Measures

The HESA data set has two measures of the graduate's socioeconomic classification prior to university enrolment: parent's occupation and a low participation neighbourhood marker (LPN). The LPN is a 0/1 dummy which indicates that the graduate comes from an area where university participation rates are less than two-thirds of the national average.[24]

To complete our SES indicators we add geographical indices of deprivation (IMD). The IMD is a relative measure of deprivation constructed by combining the following seven weighted domains of deprivation: Income, Employment, Education, Health, Crime, Barriers to Housing and Living Environment. The IMD comes at the Lower-layer Super Output Area (LSOA) level while the HESA data comes at the larger local authority district (LAD) level. Therefore, we construct our measure by averaging the IMD across all the LSOAs within each LAD.[25] For our analysis we split the IMD ranks into approximate quartiles by the year of graduation.

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[23] Although we are aware that this measure is highly dependent on the date of the survey, we feel that this is an adequate measure for teacher demand. Note that for the HESA respondents whose region we are missing, we assigned them the national average vacancy rate.

[24] Neighbourhoods in the LPM are sorted into 160 clusters based on their post code.

[25] The LSOA is a geographical area that has a minimum population of 1000 and a mean of 1500. There is an LSOA for each postcode in England. As the measure of deprivation chance over time we use 2000 for the 2000-03 cohort entry years, we use 2004 for the 2004-2006 entry years and 2007 for the 2007-09 entry years. These datasets are available in the national archives.

Therefore, IMD is an ordinal variable where Rank 1 represents the least deprived quantile of graduates and rank 4 represents the most deprived.[26]

2.4.5 Relative Wages

Using the Labour Force Survey, we calculate teacher and non-teacher wages for each Government Office Region in England by year (2003-2012).[27] We use two different methods to identify non-teachers wages. First we use the average non-teaching graduate's earnings, in a given year for a given region. Using this measure teachers' relative wages can be broadly split into three categories, these are teachers who earn: i) significantly less than the average graduate (East of England, London and South East) ii) a fairly similar amount to the average graduate (South West, East Midlands, North West and West Midlands) iii) more than the average graduate (North East and Yorkshire and the Humber).

Entry into teaching is a choice and therefore using graduates' salaries to estimate non-teachers' earnings might not reflect how much teachers would be able to earn in an alternative profession. In our second method to identify non-teachers' wages we follow Chevalier and Dolton (2004) and Fullard (2019b) and use propensity score matching (PSM) to estimate non-teachers' wages controlling for differences in observable characteristics.[28] Using this measure of teachers' relative wages teachers earn significantly more than the average non-teacher in every region apart from the: East Midlands, East of England, London and the South East.

In the DLHE, we assign each graduate a teacher and non-teacher wage based on i) the year they graduated and ii) the region of domicile or the region of the university they graduated

[26] We do not have exactly 25% in each group due to the clumping of IMD scores in the distribution.
[27] To calculate these wages, we restrict our sample to those who have a university degree, are working full time, are of working age and earn more than the national minimum wage. Teachers are identified as individuals who are working as a secondary or primary school teacher while non-teachers are graduates who are in an occupation other than teaching. We use non-teaching graduates as our comparison group because teachers in England are legally required to have a university degree therefore all occupations available to university graduates are, in principle, also available to teachers.
[28] The controls we use include, age, age squared, sex, ethnicity, degree subject and degree classification.

from. For example, for an individual who graduated in 2010 from the North West we assign them a teaching wage of £700 p/w (£36,400 p/a), a non-teaching wage of £666 p/w (£34,532 p/a), which is estimated using our first method and a non-teaching wage of £610 p/w (£32,720 p/a), estimated using our second method. We can therefore estimate teachers' relative wages at the regional level using either of our measures of non-teachers' wages by taking the difference in the natural logs (ln(Teacher Wage) – ln(Non-teacher Wage)).

As policymakers have recently made the commitment to increase teachers' initial wages to £30k (per year) by 2022 with the expressed purpose of recruiting the best and brightest graduates into teaching understanding the relationship between relative wages and the supply of graduates into initial teacher training programmes is a policy relevant question.

Table 3. Descriptive Statistics. The proportion of Graduates in our Sample of those who enrolled onto Initial Teacher Training Programs (TTP) and those who did not by observable characteristics.

Variable	On TTP	Not on TTP	Variable	On TTP	Not on TTP
Sex			**Subject**		
Male	12.0	43.9	Biology	6.5	17.7
Female	88.1	56.1	Physics	0.9	8.7
			Maths	2.1	3.6
Ethnicity			Computer Science	1.1	7.7
White	95.0	85.3	Social Studies	1.3	15.7
Black	0.5	2.0	Languages	6.3	13.1
Asian	2.8	7.9	History/Philosophy	2.4	9.9
Other	1.2	3.1	Arts	3.8	20.3
NA	0.5	1.7	Education	74.6	2.7
			Combined	1.0	0.7
Degree Classification[+]			**IMD**		
1st	7.7	14.8	Score	21.4	20.7
2:1	51.6	54.1	Rank 1 (least Deprived)	20.3	24.1
2:2	37.2	26.3	Rank 2	24.0[Y]	23.7
Institution			Rank 3	29.7	31.7
Oxbridge	0.4	3.8	Rank 4 (most Deprived)	24.0	22.4
Russell Group	1.8	25.5			
Non Russell Group	98.2	75.5	Low Participation Neighbourhood	11.7	8.4
State School Educated	96.1	85.8			

These differences are all statistically significant at the 1% level apart from those that are marked with a Y, which are not statistically significant. [+]We are missing nine respondent's degree classifications. We include them in our unclassified group (n=4377). Our results do not change if we do, or do not, include them.

2.5 Results

2.5.1 Descriptive Statistics of graduates going into Initial Teacher Training Programmes

In our sample, 4.5% (33,400) of our graduates enrol onto TTPs. The characteristics of those who enrolled onto TTPs are shown in table 3, along with a comparison of the graduates who did not enrol. Female (88% vs 56%), white (95% vs 85%) and state school educated (96% vs 86%) graduates are over-represented among those enrolling onto TTPs. They also tend to have worse degree classifications (52% vs 54% with a 2:1, 37% vs 26% with a 2:2 and 8% vs 15% with a 1st), and come from less prestigious institutions relative to the overall population of graduate (0.4% vs 4% from Oxbridge and 1.8% vs 26% from Russell Group). We also find that graduates who enrol onto TTPs have a UCAS tariff that is, on average, 50 points lower, significant at the 1% level.[29,30] Most of the graduates who enrol onto TTPs have a Degree in Education (75% vs 3%) followed by Biology (7% vs 18%), Languages (6% vs 13%) and Arts (4% vs 20%). The smallest group is physics (1% vs 9%). While there are also modest differences in representation on TTPs among the least deprived (20% vs 24%) and among the most deprived (24% vs 22%). Furthermore over 12% (vs 8%) are from low participation neighbourhoods (LPN).

Table 4 shows that the quantity of graduates enrolling onto TTPs varies both by year and observable characteristics. Column 1 shows that enrolment is highest between 2009 and 2011 while the remaining columns report the ratio of those enrolled onto TTPs against those who are not, by characteristics and by graduation year.[31] For example, column 3 shows that among 2003 graduates, 51% of those on TTPs have a 2:1 degree, and 51% of those not on a TTP, so the ratio is 1.00. Between 2004 and 2009 the proportion with a 2:1 degree was lower among those on TTPs than those who were not, but by 2012 it was 6% higher. Column 2 shows that first class degrees were always under-represented among those on TTPs, but catching up fast between 2009 and 2012.

[29] The UCAS Tariff is an aggregate indicator of the student's pre-university attainment. Specifically it assigns each student a numerical score based on the grades and qualifications achieved. Its purpose it to make achievements in different qualifications directly comparable. A higher UCAS Tariff indicates higher attainment.

[30] A 50 point difference in UCAS tariff is roughly similar to the difference between a student achieving A*A*A in their A-levels and someone achieving BBC.

[31] (Percentage of graduates on a TTP who have degree classification x)/(Percentage of gradates not on a TTP who have degree classification x). A figure closer to 1 means that the two groups have a more similar distribution of x, a figure less than a means that the proportion of graduates with x is higher in the non-TTP group while a figure greater than one indicates that the proportion in the TTP group with x is higher than the non-TTP group. We use odds ratios to account for the fact that the proportion of graduates with certain characteristics, such as a 1st class degree, change over time.

Table 4 Equality of means across time. The figures presented are ratios (the percentage of TTP with each category/the % of non TTP) by a Graduates degree Classification, Sex and SES.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
		Degree Classification				Sex	IMD SES Rank					Ethnicity		
Grad Year	Quantity going into TTP (as a % of graduate)	first Class Degree	2:1 Degree	2:2 Degree	3rd Degree	Male	1 (Least deprived)	2	3	4 (Most Deprived)	Low Participation area	White	Black	Asian
2003	3,585 (5.44%)	0.43	1.00 Y	1.30	0.60	0.29	0.88	0.99	1.11	1.02 Y	1.37	1.11	0.23	0.32
2004	2,775 (4.33%)	0.37	0.95	1.41	0.87Y	0.24	0.86	1.03 Y	1.09	1.03 Y	1.41	1.12	0.26	0.24
2005	2,780 (4.32%)	0.40	0.86	1.54	1.00 Y	0.28	0.85	0.91	1.13	1.13	1.55	1.13	0.26	0.27
2006	2,755 (4.10 %)	0.40	0.89	1.53	0.87 Y	0.25	0.80	1.03 Y	1.08	1.10	1.49	1.11	0.34	0.28
2007	3,230 (4.62 %)	0.40	0.90	1.51	0.95 Y	0.26	0.84	1.00 Y	1.10	1.08	1.41	1.10	0.28	0.37
2008	3,540 (4.65%)	0.44	0.91	1.54	0.82	0.27	0.79	0.99 Y	1.13	1.12	1.52	1.11	0.22	0.37
2009	3,830 (4.94%)	0.48	0.95	1.46	0.89 Y	0.26	0.87	0.99 Y	1.11	1.06	1.46	1.10	0.30	0.47
2010	3,865 (4.78%)	0.51	0.98 Y	1.41	0.77	0.30	0.84	1.03 Y	1.08	1.06	1.32	1.12	0.25	0.37
2011	3,735 (4.35%)	0.70	1.02 Y	1.27	0.43	0.26	0.87	1.02 Y	1.08	1.03 Y	1.28	1.11	0.25	0.39
2012	3,310 (3.68%)	0.84	1.06	1.10	0.33	0.29	0.79	1.14	1.03	1.06	1.34	1.12	0.19	0.38

The closer the ratio is to 1 the more similar the means are. Figures under 1 mean that they are underrepresented on TTP while figures over 1 mean they are overrepresented on TTP. All of the mean differences between the TTP and non TTP groups are statistically significant unless marked with a Y which means there is no statistically significant difference between TTP and non TTP means. The frequencies are all rounded to the nearest 5 or 0 as required by the data providers.

Column 4 shows that lower second-class degrees are always over-represented among those on TTPs, but the difference is falling significantly from 2010 to 2012. We also observe that men and the least deprived graduates are consistently under-represented (column 6 and 9) while white graduates are consistently over-represented (table 4 column 12).

In our data, we observe a higher proportion of Black graduates graduating year on year, yet, from 2007, we observe a general decline in the proportion of black graduates enrolling onto teacher training (table 4 column 13). While Asians' participation rates remain relatively consistent, the proportion on TTPs increases significantly over time (column 14).

2.5.2 Bad Economy, More Teachers?

Estimates of the effect of graduating during a period of high unemployment based on the different models discussed in section (3) are presented in Table 5. Column 1 shows our first model (equation 1), and we build from this by adding our graduate specific covariates (column 2) and other controls that might affect the cohort composition and the decision to go into teaching (column 3) until we reach our preferred specification in column 4 (equation 2). In all of these specifications we find that unemployment has no effect on the probability of enrolling on a TTP.

Table 5. The effect of the unemployment rate, at time of graduation, on the probability of enrolling onto a teacher training program.

	(1)	(2)	(3)	(4)
Unemployment Rate 0-100	-0.00056	-0.0006	-0.00061	-0.00166
	(-0.00096)	(-0.00095)	(-0.00095)	(-0.00111)
Year FE	X	X	X	X
Region FE	X	X	X	X
Institution FE	X	X	X	X
Subject FE	X	X	X	X
Individual Controls		X	X	X
Claimant Count			X	X
Vacancy Rate			X	X
Subject TT's				X
Constant	0.0452**	0.0495**	0.0551***	0.0258
	(-0.0204)	(-0.0206)	(-0.0204)	(-0.0207)
N	741815	741815	741815	741815
DV mean	0.045	0.045	0.045	0.045
(SD)	(0.207)	(0.207)	(0.207)	(0.207)

Source: DLHE data on the selected sample described in section 4 linked with the subject specific unemployment rate derived from the Labour Force Survey and the Office for National Statistics data.
Note: Individual controls include: sex, ethnicity, degree classification and IMD rank. Claimant count is the unemployment rate, measured by the claimant count, the year prior to university enrolment. Vacancy Rate is the number of teaching vacancies, at year of graduation, as a proportion of total teachers (by region). Robust standard errors are clustered at the degree subject year level and reported in brackets. * p<0.10 , ** p<0.05, *** p< 0.01

Table 6 Lag and lead unemployment rate on the probability of enrolling onto a teacher training program.

	(1)	(2)	(3)	(4)	(5)	(6)
	Year before graduation		Year of graduation		Year after graduation	
Unemployment Rate 0-100	0.00111 (-0.00087)	0.00123 (-0.00093)	-0.0009 (-0.00094)	-0.00083 (-0.00075)	-0.00115 (-0.00086)	-0.00102 (-0.00082)
Year FE	X	X	X	X	X	X
Region FE	X	X	X	X	X	X
Institution FE	X	X	X	X	X	X
Subject FE	X	X	X	X	X	X
Subject TT		X		X		X
Constant	-0.0241 (-0.0155)	-0.0277 (-0.0194)	-0.0163 (-0.0149)	-0.0203 (-0.019)	-0.0154 (-0.0144)	-0.0198 (-0.019)
N	586027	586027	586027	586027	586027	586027
DV mean (SD)	0.045 (0.207)	0.045 (0.207)	0.045 (0.207)	0.045 (0.207)	0.045 (0.207)	0.045 (0.207)

Source: DLHE data on the selected sample described in section 4 linked with the subject specific unemployment rate derived from the Labour Force Survey and the Office for National Statistics data. Columns 1 and 2 use the unemployment rate the year prior to graduation (i.e. the 2008 graduates are assigned the 2007 subject specific unemployment rate), columns 3-4 use the unemployment rate of the year of graduation and columns 5-6 use the unemployment rate the year after graduation.
Note: The sample size is reduced because we drop the 2003 and 2012 graduates as we cannot assign them a lagged and lead unemployment rate respectively. Robust standard errors are clustered at the degree subject year level and reported in brackets. * p<0.10 , ** p<0.05, *** p< 0.01

The lack of any effect of the unemployment rate might be because the unemployment rate measured at the year of graduation might not capture the labour market conditions that graduates faced when they decided to apply for teaching. The application round for TTPs for a given graduate cohort opens in the October of the year prior to graduation and over half of applications have already been submitted by the end of the year. Therefore, it might be more appropriate to assign graduates the unemployment rate the year prior to graduation ($U_{f,t-2}$). It is also possible that the unemployment rate is a lag of labour market conditions and, to get an accurate sense of the labour market conditions these graduates face, it might be more appropriate to use the unemployment rate the year after graduation ($U_{f,t+1}$).

Columns 1 and 2 (5 and 6) in table 6 report the coefficient using a one year lagged (lead) unemployment rate. Similar to our estimates using the unemployment rate from the year of graduation (columns 3 and 4) we observe a precisely estimated no effect.

Another check we perform is to consider variation at the regional level. Instead of using our subject specific unemployment rate, which assumes that all graduates, for a given cohort and degree subject, face the same labour market conditions, it might be more appropriate to use a regional unemployment rate. Relaxing our assumption about perfect graduate mobility and exploiting across regional variation in the regional unemployment rate (home or university) we estimate equation 4.

Columns 1 to 2 and 3 to 4 in table 7 show the effect of a 1pp increase in the graduate unemployment rate, at the home and university region respectively, on the probability that a graduate will be enrolled onto a TTP. Across all of these specifications we observe that graduating during a period of high unemployment (measured at the regional level) has a very small effect on the probability of enrolling onto a TTP and this is statistically indistinguishable from zero.

The prevalence of a statistically insignificant estimate of labour market conditions on the probability that a graduate will enrol onto a TTP is not, necessarily, unexpected. This is because of capacity constraints. If we had data on application behaviour for this period we would expect to see a positive effect, but we only observe enrolment. We will discuss this in detail in section 7. Next we consider whether labour market conditions at graduation might affect the composition of graduates on TTPs.

Table 7 The effect of the regional unemployment rate on TTP enrolment

	(1)	(2)	(3)	(4)
Area	Home Region		Uni Region	
Unemployment rate 0-100	-0.00000661 (0.000220)	-0.0000332 (0.000227)	-0.000376 (0.000258)	-0.000367 (0.000266)
Controls	X	X	X	X
Year FE	X	X	X	X
Region FE	X	X	X	X
Institution FE	X	X	X	X
Subject FE	X	X	X	X
Region TT		X		X
Constant	0.0513*** (0.0132)	0.0503*** (0.0131)	0.0703*** (0.0191)	0.0694*** (0.0190)
N	686937	686937	734511	734511
DV mean (SD)	0.045 (0.207)	0.045 (0.207)	0.045 (0.208)	0.045 (0.208)

Source: DLHE data on the selected sample described in section 4 linked with the regional unemployment rate derived from the Labour Force Survey and the Office for National Statistics data.

Note: Our controls are: sex, ethnicity, degree classification, regional vacancies and IMD rank. Specification 1 and 2 using the unemployment rate based on the graduatesR. Specifications 3 and 4 use the unemployment rate based on the region of the university they attended. Robust standard errors are clustered at the year region level, where the region differs depending on if we are using the university or home unemployment rate and reported in brackets. * p<0.10 , ** p<0.05, *** p< 0.01

Table 8 Heterogeneity analysis by observable characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
Characteristic	Male	White	Low Participation Region	Low SES	Degree 2:1 or above	Russell Group
Characteristic* Unemployment Rate	0.0101*** (0.00352)	-0.0142*** (0.00490)	0.00229 (0.00144)	0.00232** (0.00114)	-0.00724** (0.00280)	0.0169*** (0.00486)
Unemployment rate	-0.00659*** (0.00242)	0.0103*** (0.00373)	-0.00185 (0.00115)	-0.00191 (0.00118)	0.00333* (0.00172)	-0.00522*** (0.00187)
Constant	0.0374* (0.0216)	-0.0263 (0.0255)	0.0304 (0.0207)	0.0309 (0.0207)	0.00852 (0.0217)	0.0503** (0.0209)
N	741815	741815	741815	741815	741815	741815
DV mean (SD)	0.045 (0.207)	0.045 (0.207)	0.045 (0.207)	0.045 (0.207)	0.045 (0.207)	0.045 (0.207)

Source: DLHE data on the selected sample described in section 4 linked with the subject specific unemployment rate derived from the Labour Force Survey and the Office for National Statistics data.

Note: Our regression include year fixed effects, region fixed effects, institution fixed effects, subject fixed effects and subject degree time trend. In addition we control for: sex, ethnicity, degree classification, regional vacancies and IMD rank. Specification 1 and 2 interacts male and white dummies with the unemployment rate. Specifications 3 and 4 interact a low participation dummy (indicates if the graduates is from a region where university participation is less than two thirds of the national average) and a low SES dummy (defined as been from a home whose parents are either in a semi-routine, routine occupation or long term unemployed). Specifications 5 and 6 interact Degree 2:1 or above and Russell Group dummies with the unemployment rate. Robust standard errors are clustered at the degree subject year level and reported in brackets. * p<0.10 , ** p<0.05, *** p< 0.01

2.5.3 Bad Economy, More Diverse Teachers?

Now we turn to possible heterogeneity in the effect of the unemployment rate at graduation on enrolment behaviour by interacting indicators for sex (table 8 column 1) and ethnicity (column 2) with the subject specific unemployment rate in equation 2. These results show that the unemployment rate impacts enrolment behaviour differently according to these individual characteristics. Specifically an increase in the unemployment rate increases the probability that a male graduate will enrol onto a TTP by 1pp, relative to female graduates, while it decreases the probability that a white graduate will enrol by 1.4pp, relative to non-white graduates.[32]

Similar to many western countries, the school workforce is fairly homogeneous (female and white) and struggles to attract male graduates and graduates from ethnic minority backgrounds into the profession. An increase in the unemployment rate makes teaching more appealing to everyone. In response to this boost in interest, TTP providers are unable to recruit additional graduates, due to capacity constraints, but a more diverse pool of applicants results in a more diverse cohort of trainee teachers.

We are also interested in whether the effect differs by a graduate's socioeconomic status measured by our indicator for higher education participation in the area (column 3) or parental occupation (column 4).[33] These results show that graduates from less affluent backgrounds differ in their enrolment behaviour in response to an increase in the unemployment rate relative to their more affluent peers. Although the magnitude of the effect is fairly small, an increases in the unemployment rate increases the probability that a graduate from a low SES household will enrol by 0.2pp (column 4), relative to their more affluent

[32] Note that a relatively small number of non-white graduates (1.57%) go into teaching so, while the coefficient is positive, it is difficult to get a good idea of the effect size.
[33] The parent occupation dummy indicates whether graduates come from a household where their parents are employed in either a semi-routine or routine occupation or they are long term unemployed.

peers. Therefore an increase in the unemployment rate is unlikely to have a transformative effect on the SES composition of trainee teachers.

2.5.4 Bad Economy, Better Teachers?

Next we investigate whether the effect on the composition of graduates enrolled onto TTPs is likely to be welfare improving for pupils. Empirical evidence shows that low quality teachers negatively affect pupils to the same, or greater, extent that high quality teachers improve pupil outcomes. Therefore, any impact on the supply of teachers (through retention and/or recruitment) is only welfare improving for students if it, on average, improves teacher quality (Hanushek et al., 2015, Hanushek and Woessmann 2011).

Unlike Nagler et al., (2015), who uses pupil performance to create a value-added measure of teacher quality, we are unable to directly measure the quality of teachers. But we can use a graduate's degree classification and the selectivity of the university they attended as a proxy. As policymakers are trying to recruit more graduates: i) from more prestigious institutions ii) with higher degree classifications into teaching we will assume that an increase (decrease) in graduate quality measured by i) and/or ii) is welfare improving (decreasing). Although, with the exception of experience, it is difficult to identify teacher quality based on observable characteristics (Rivkin et al., 2005, Wiswall 2013) we feel that this assumption is reasonable due to policymakers current recruitment objectives and the strong relationship between teachers' cognitive skills and student performance (Hanushek et al., 2014).

Now we turn to possible heterogeneity in the effect by the graduate's degree classification (table 8 column 5) and the prestige of the university they attended (column 6). The interactions indicate that an increase in the unemployment rate has a negative effect on the probability that a graduate with a 2:1 or above will enrol on a TTP (0.7pp), relative to graduates with a 2:2 or below, and has a positive effect on graduates from a Russell Group university (1.69pp), relative to non-Russell Group graduates. These results demonstrate that a 1pp increase in the unemployment rate decreases the probability that a graduate with a 2:1 or above will enrol on a TTP (0.39pp) and increases the probability that a graduate from a Russell group university will enrol on a TTP (1.16pp).[34] The modest negative effect we observe for graduates with a 2:1 or above might be driven by the boost in enrolment from graduates from more prestigious universities due to less grade inflation in more prestigious institutions.[35]

While we are unable to confirm that the compositional effect brings teachers into the profession who are more effective at raising pupil test scores, we can confirm that it increases the proportion of graduates from more selective universities which is likely to be welfare improving for pupils (Ehrenberg and Brewer 1994, Ferguson 1991). Indeed we would expect an increase in the pool of potential teachers to improve the quality of enrolees as the TTP selection process (assessments, interviews, practical assignments) is intended to select the most suitable graduates.

2.5.5 Bad Economy, More Subject Specialist Teachers?

The school workforce in England overwhelmingly consists of general teaching professionals rather than subject specialists - 75 percent of graduates on a TTP have an undergraduate degree in Education. Policymakers struggle to recruit subject specialist teachers, particularly those with Physics degrees. Therefore, we would expect a boost in applications for TTPs, caused by a tougher graduate labour market, to decrease the probability that a graduate with a degree in Education will be enrolled onto a TTP and increase the probability that a subject specialist will be enrolled. Specifically, a boost in the number of graduates interested in a

[34] Note that few Russell Group graduates go onto TTPs (0.01%) therefore it is difficult to get a good sense of the magnitude of the effect size.
[35] Between 2003 and 2012 the proportion of non-Russell group graduates who were awarded a first class degree increased by 72% (compared to 35% of Russell group).

career in teaching from a wide range of academic backgrounds will increase the subject diversity of those enrolled onto TTPs.

Table 9 Heterogeneity by subject

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Sample	Biological Sciences	Physics	Math	Computer Sciences	Social Studies	Languages	History/Philosophy	Arts	Education	Combined
Unemployment rate	0.00163	0.00226*	0.000149	0.000271	0.00768***	0.000136	0.00132	0.000225	-0.0358*	0.000225
	(0.00137)	(0.00115)	(0.00084)	(0.00029)	(0.00174)	(0.0003)	(0.00086)	(0.0003)	(0.0177)	(0.00242)
Wild Cluster p-values	[0.4797]	[0.4738]	[0.8888]	[0.4750]	[0.1162]	[0.5687]	[0.4187]	[0.5779]	[0.3537]	[0.9366]
Wild cluster CI's	[-.003999, .007791]	[-.004927, .009165]	[-.002465, .003001]	[-.001768, .002791]	[-.003898, .01206]	[-.001059, .0008665]	[-.002429, .00543]	[-.004183, .002665]	[-.1158, .04352]	[-.009193, .009642]
Constant	0.0284***	-2.9E-05	0.0367**	0.0192***	-0.0106**	0.0404***	0.0190***	0.0165***	0.135*	0.0195
	-0.00735	-0.00293	-0.0124	-0.00387	-0.00351	-0.00556	-0.00285	-0.00382	-0.0714	-0.0124
N	127223	62266	26270	55013	111591	94563	70751	145117	43914	5107
DV mean (SD)	0.0171 (0.129)	0.0049 (0.070)	0.027 (0.162)	0.00669 (0.081)	0.0038 (0.062)	0.0222 (0.147)	0.0111 (0.105)	0.0087 (0.093)	0.567 (0.495)	0.064 (0.245)

Source: DLHE data on the selected sample described in section 4 linked with the subject specific unemployment rate derived from the Labour Force Survey and the Office for National Statistics data.

Note: Our regression include Region Fixed Effects, Institution Fixed Effects, Time Trends and our usual controls: sex, ethnicity, degree classification, regional vacancies and IMD rank. Robust standard errors are clustered at the year level and reported in parenthesis with stars indicating statistical significant at the usual levels: * p<0.10 , ** p<0.05, *** p< 0.01. In square brackets we report the wild bootstrap cluster p-values and 95% confidence intervals, using 1,000 repetitions.

This is what table 9 shows. A 1pp increase in the unemployment rate increases the probability that a Physics (social studies) graduate will enrol onto a TTP by 0.2pp (and 0.8pp), columns 2 and 5 respectively, and decreases the probability that an Education graduate will enrol by 0.36pp (column 9). As outlined above, our standard errors for our subsample analysis (equation 3) are clustered at the cohort level. To adjust for the small number of clusters we also report the wild bootstrap cluster p-values and 95% confidence intervals (using 1,000 repetitions).

Our subsample analysis shows that the unemployment rate has a positive effect on the probability that a Physics and Social Studies graduate will enrol onto a TTP. However the subject specific specifications might be too noisy to get a good idea of the effect size (i.e. less than 1 percent of graduates from these subjects enrol).

To assess the possible effect size, in table 10, I interact a STEM dummy with the unemployment rate. While the effects are initially positive (column 1 shows equation 1) when we include subject fixed effects and build up to our preferred specification (column 4 which shows equation 3) we find a precisely estimated no effect. The likely cause of this is that Physics and Social Science graduates make up a fairly small proportion of STEM and Non-STEM graduates respectively (the groups we find positive effects for) so when we combine them together it becomes difficult to find an effect.

Table 10 Heterogeneity analysis by STEM vs Non-STEM

	(1)	(2)	(3)	(4)
STEM*				
Unemployment	0.0540***	0.0540***	-0.00147	-0.000450
Rate	(0.0190)	(0.0190)	(0.00187)	(0.00128)
Unemployment rate	-0.0622***	-0.0622***	-0.000386	-0.00158
	(0.0142)	(0.0142)	(0.00105)	(0.00122)
Controls	X	X	X	X
Year FE	X	X	X	X
Region FE	X	X	X	X
Institution FE	X	X	X	X
Time Trend		X	X	
Subject FE			X	X
Subject TT				X
Constant	0.233***	0.233***	0.0547***	0.0257
	(0.0530)	(0.0530)	(0.0204)	(0.0207)
N	741815	741815	741815	741815
DV mean	0.045	0.045	0.045	0.045
(SD)	(0.207)	(0.207)	(0.207)	(0.207)

Source: DLHE data on the selected sample described in section 4 linked with the subject specific unemployment rate derived from the Labour Force Survey and the Office for National Statistics data.
Note: Our controls are: sex, ethnicity, degree classification, regional vacancies and IMD rank. Our specifications interact a STEM dummy with the unemployment rate. Robust standard errors are clustered at the degree subject year level and reported in brackets. * p<0.10 , ** p<0.05, *** p< 0.01

Table 11 Teachers relative wages and enrolment onto a TTP

	(1)	(2)	(3)	(4)
	Home region		University Region	
Relative Wage (match)	0.00143		-0.000774	
	(0.00561)		(0.00632)	
Relative Wage (grad)		-0.00917		-0.0176
		(0.00921)		(0.0111)
Controls	X	X	X	X
Year FE	X	X	X	X
Region FE	X	X	X	X
Institution FE	X	X	X	X
Subject FE	X	X	X	X
Region TT	X	X	X	X
Constant	0.0503***	0.0484***	0.0679***	0.0646***
	(0.0130)	(0.0129)	(0.0188)	(0.0188)
N	686937	686937	734511	734511
DV mean	0.045	0.045	0.045	0.045
(SD)	(0.207)	(0.207)	(0.208)	(0.208)

Source: DLHE data on the selected sample described in section 4 linked with the regional relative wages derived from the Labour Force Survey and the Office for National Statistics data.

Note: Our controls are: sex, ethnicity, degree classification, regional vacancies and IMD rank. Specification 1 and 2 using the relative wages based on the graduates home region. Specifications 3 and 4 use the wages based on the region of the university they attended. Robust standard errors are clustered at the year region level, where the region differs depending on if we are using the university or home unemployment rate and reported in brackets. * p<0.10 , ** p<0.05, *** p< 0.01

2.5.6 Higher Wages, More Teachers?

In table 11, we estimate equation 5 using our matched relative wage (column 1 and 3) and graduate relative wage (column 2 and 4) at the home domicile (columns 1 and 2) and university (column 3 and 4) regions. As with unemployment rates, relative wages are found to have no effect on the probability that a graduate will be enrolled onto a TTP six months after graduation.

Interestingly we do find a positive relationship between teachers' relative wages at the time of university enrolment and the probability of a graduate enrolling onto an undergraduate programme in Education (table 12 column 1 and 2). This does show that young people from regions where teachers' relative wages are higher are more likely to enrol on an undergraduate programme in Education. However, the effect does disappear when we include our region fixed effects and time trends (column 3 and 4) which suggests that the effect is driven by some other unobservable, such as regional differences in degree preferences, which is correlated with teachers' relative wages.

Table 12 Relative wages on the probability of enrolling onto a degree in education

	(1)	(2)	(3)	(4)
Relative Wage (grad) at time of uni enrolment	0.139***	0.0422***	0.00354	0.00279
	(0.0113)	(0.00831)	(0.0125)	(0.0104)
Controls	X	X	X	X
Year FE	X	X	X	X
Institution FE		X	X	X
Region FE			X	X
Region TT				X
Constant	0.151***	0.0513***	0.0505***	0.0519***
	(0.00473)	(0.00183)	(0.00227)	(0.00208)
N	547449	547449	547449	547449
DV mean	0.064	0.064	0.064	0.064
(SD)	(0.245)	(0.245)	(0.245)	(0.245)

Source: DLHE data on the selected sample described in section 4 linked with the regional relative wages, from the year of enrolment, derived from the Labour Force Survey and the Office for National Statistics data. Our sample size is reduced because we only have the relative wages, at year of enrolment, for the 2006-2012 graduate cohorts.

Note: Our relative wage measure is the difference in the logged teachers and non-teaching graduate's wages. Our dependent variable is a dummy that indicates if a graduate has enrolled onto a undergraduate program in education, or not. Our controls are: sex, ethnicity, degree classification, regional vacancies, unemployment rate at time of enrolment and IMD rank Robust standard errors are clustered at the year region level, where the region is the home region, and reported in brackets. * p<0.10 , ** p<0.05, *** p< 0.01

Table 13 Linear vs non-linear specification

	(1)	(2)	(3)
Specification	OLS	probit	logit
Unemployment Rate (0-100)	-0.00157	-0.000629	-0.000367
	(0.00110)	(0.000432)	(0.000515)
Male	-0.0163***	-0.0216***	-0.0229***
	(0.00217)	(0.00140)	(0.00162)
Degree 1st Class	-0.00357	-0.00581**	-0.00459
	(0.00219)	(0.00245)	(0.00296)
Degree 2:1	0.000470	-0.000482	0.000521
	(0.00201)	(0.00135)	(0.00141)
Degree 3rd Class	-0.0158***	-0.0139***	-0.0143***
	(0.00328)	(0.00155)	(0.00149)
Controls	X	X	X
Year FE	X	X	X
Region FE	X	X	X
Institution FE	X	X	X
Subject FE	X	X	X
Subject TT	X	X	X
N	741815	741815	741815
DV mean	0.045	0.045	0.045
(SD)	(0.207)	(0.207)	(0.207)

Source: DLHE data on the selected sample described in section 4 linked with the subject specific unemployment rate derived from the Labour Force Survey and the Office for National Statistics data.

Note: Our controls are: sex, ethnicity, degree classification, regional vacancies, unemployment rate the year prior to enrolment and IMD rank.. For the institution FE's I use a higher level to ensure that stata does not drop observations so that the coefficients are comparable. The Russell Group institutions are split into quintiles by size and non-Russell group institutions are split into twenty categories by size. Robust standard errors are clustered at the degree subject year level and reported in brackets. * p<0.10 , ** p<0.05, *** p< 0.01

2.6 Robustness Check

For our main model we decide to use a linear specification. However, a non-linear model might be more appropriate in our setting as only a small proportion of our sample enrol onto TTPs. In Table 13 we compare the effect of a 1pp increase in the unemployment rate, and a selection of covariates, on the probability of enrolling onto a TTP using linear (column 1) and non-linear specifications (column 2 probit and 3 logit).

These estimates show that when we use our preferred model (equation 2) we find that graduating during a period of decreased labour demand has no effect on the probability of going into a TTP across our specifications. Therefore we are confident that our estimates are not driven by our decision to use a linear specification. Looking at our other covariates we observe that male graduates are less likely to go into teaching as are those with a 3rd class degree.[36]

2.7 Discussion and concluding remarks

In this paper we use the variation in the unemployment rate at time of graduation to investigate the effect that labour market conditions have on enrolment onto Initial Teacher Training Programmes (TTPs) for 10 graduate cohorts (2002/03-2011/12) in England.

Our main result is that enrolment on a TTP does not respond to periods of low labour demand. While it is almost certainly true these periods do boost the number of graduates interested in teaching for instance, the Covid-19 induced recession increased the number of applicants to teacher training programmes for the 2019/20 round by 65% (see Figure A1 in the appendix), we found no impact on enrolment, and we suspect that this is due to capacity

[36] Note that the institution fixed effects we use in this section is at a higher level to ensure that none of our dummies perfectly predict failure and are therefore dropped from our regression. The institution fixed effects in this specification are grouped using the following: Russell Group institutions are split into quintiles by size and non-Russell group institutions are split into twenty categories by size.

constraints.[37] Each year roughly half of applications are not placed on a TTP programme. The reason so many are rejected is because, for each trainee teacher, providers must secure school based placements - often two twelve week placements as well as multiple shorter placements. Sourcing placements can be tricky as many schools are reluctant to take on trainee teachers, as it is costly to them, and providers have a limited number of schools they can place students as all placements must be in a similar geographical region to the TTP provider. [38,39]

In a wider context, these results indicate that any boost in the relative attractiveness of teaching, in terms of earnings, will only increase the supply of teachers as long as there is capacity in the system to accommodate these applicants. This means that any boost in the number of graduates interested in going into teaching will only impact teacher supply if it happens to coincide with a period of prolonged shortages (such as policymakers failure to meet recruitment targets between 2013 and 2019). But even then, any increase in supply, due to a recession, for example, will be mitigated by the reduction in attrition (teacher attrition is also pro-cyclical). If policymakers want to take advantage of any boost in applications they need to ensure that there are enough schools willing to place these trainees, they could do this by providing schools with incentives to take trainee teachers.

Our heterogeneity analysis suggests that an increase in the graduate unemployment rate has a positive effect on the diversity of trainee teachers. In a general sense, this is beneficial as there are numerous advantages to a diverse workforce. Specifically, this may positively benefit boys, who underperform at school relative to girls, as there is some evidence of role

[37] There is no publically available data on teacher training applications for our time period so we are unable to check.

[38] Many schools are unwilling to take on trainee teachers because it is costly to the school: i) trainee teachers are paired with a mentor (a senior teacher) who is required to go through additional training ii) trainee teachers require additional support and mentoring for the duration of their placement which increases the workload of existing teachers iii) teacher quality (measured by the ability to improve student outcomes) increases with experience therefore many schools are unwilling to take on trainee teachers due to the potentially negative impact it might have on their academic rankings.

[39] Moreover, the ability for providers to find school placements tends to become more difficult during periods of high unemployment. Attrition from teaching is procyclical, when there are fewer employment opportunities teachers are less likely to quit, which means that the demand for trainee teachers might actually fall.

model effects - male students performing better with male teachers - in England (Hermann 2017).[40]

In addition, our heterogeneity analysis raises questions about whether making teaching more attractive (paying more) is welfare improving for students in England. Our results show a positive effect for subject specialist teachers (Physics) and Russell Group graduates but we also find a negative effect for graduates with a 2:1 or above. Further research is needed to establish if the compositional effect we observe is welfare improving for students. This is particularly important in our setting where existing research suggests that some of the methods used to identify the quality of potential teachers, such as the professional skills test, are largely uncorrelated with the ability to improve student outcomes. Therefore a project looking at the effectiveness of teachers in England using a new dataset seems like a promising topic of future research.

In this paper we test the hypothesis that graduates enrol into Teacher Training during periods of low economic activity because the demand for teachers is largely unrelated to economic conditions. As existing evidence shows that the supply of teachers and other public sector professions, such as nurses, is responsive to economic conditions we are confident that this is a plausible mechanism (Konetzka et al., 2018, Li et al., 2019). However, in our case, we are looking at enrolment into Teacher Training – a form of postgraduate study. It is also plausible that during periods of low labour demand graduates might enrol into any form of education, not just teacher training, to avoid becoming unemployed.

We do not have data on applications to teacher training, or any other postgraduate qualifications, so we cannot distinguish between these two mechanisms. However we do

[40] In the USA Dee (2007) finds that same-gender teachers significant improves the achievement of both boys and girls. Further research needs to be done to be done to estimate the welfare effects from an increase in gender diversity for teachers in England as it is possible that the positive effects for having more male teachers (for male students) could be offset by the impact on female students.

control for teacher demand in our regressions and find a persistent negative, albeit small, statistically significant effect which suggests that the demand for teachers does influence the graduate's decision to enrol. Further research is needed to investigate how the change in demand for teacher training, during periods of low economic activity, compares to the change in demand for other postgraduate qualifications.

Our data does not allow us to identify attrition rates, given that existing evidence suggests that those who graduate during a recession have higher occupational mobility (more likely to switch jobs earlier) future research is needed to determine if recessions have a lasting impact on the supply of teachers (Shvartsman 2018, van den Berge and Brouwers 2017).

Finally, our data does not allow us to identify which teacher training route, or course, graduates enrol onto. As there has been a significant expansion in salaried training routes over the last few years, it would be interesting to know if the increase in the cost associated with the traditional training route (PGCE) has influenced either the decision to enrol, or which programme graduates enrol onto.[41]

[41] As far as we are aware Fullard (2019a) and Castro-Zarzur et al., (2019) are the only paper that investigates the effect of tuition fees on teacher supply. The former is in our setting and paper finds that the increase in tuition fees has a negative effect on the probability that a graduate will enrol, where the effect is significantly stronger for male graduates. But the data they use does not allow them to identify which programmes graduates enrol onto.

Chapter 3

Relative Wages and Pupil Performance, evidence from TIMSS

3.1 Introduction

Do teachers' relative wages make a difference to pupil outcomes? This is an important policy question in general, as it is widely established that teachers are the most important school input in the education production function (Chetty et al., 2011, Hanushek 2011a, b, Hanushek et al., 2015, Rivkin et al., 2005). But it is specifically important in the English setting, where the school workforce has faced significant challenges from a decline in quantity (England has faced significant teacher shortages almost continually since the 1940s (Dolton et al., 2003)), to a decline in quality (teachers today are more likely to have lower levels of prior attainment compared to non-teaching graduates (Chevalier and Dolton 2004)).

The literature suggests that there several reasons why teachers' wages might influence pupil outcomes. The first is through occupation choice. When teachers' wages improve, so does the quality of individuals who enter teaching. As teacher quality is the main determinant of school quality (Hanushek 2004), a change in the pecuniary benefits of teaching could impact pupil outcomes through this channel.

Existing evidence suggests that higher salaries improve pupil outcomes by attracting higher quality teachers into the profession. Using a rich administrative dataset linked to pupil test scores Nagler et al., (2015) found that teachers in Florida who joined the profession during a recession (when teaching was relatively more attractive than alternative occupations) were systematically better at raising their pupils' test scores. In the UK this is supported by Nickell and Quintini (2002) who found that the decline in the relative pay of public sector workers in the 1970s and 1980s led to a decline in the quality of men, measured by prior levels of academic attainment, entering teaching.

The second strand of the literature investigates whether wages can be used to motivate existing teachers to work harder, or more productively, in a way that meaningfully affects pupil outcomes. Labour economists have long theorized about how wages can affect labour productivity using efficiency wage models e.g. Shapiro and Stiglitz (1984). An example of how this could occur is through reduced shirking. Effort is costly to the teacher and difficult to monitor, therefore teachers may decide to shirk. But when teachers' wages increase, the outside option becomes less attractive, and the cost of shirking increases. Another possibility is that higher relative wages might improve labour productivity by decreasing the likelihood that an employee has a second job – allowing them to focus on their main job. There is evidence that higher wages decrease the instances of teachers holding a second jobs in Indonesia (De Ree et al., 2015). However, this is unlikely to be a mechanism in our setting as only 6% of Secondary School and 3% of Primary School teachers have second jobs according to the 2019 Labour Force Survey (LFS).[42]

A final mechanism is that workers respond to an increase in relative wages by improving their productivity due to a fall in perceptions of inequity (Akerlof 1982). According to this hypothesis, when workers feel they are more valued, through a higher relative wage, they work harder. There is suggestive empirical evidence that concerns about fairness and equity do influence effort, see Fehr et al., (2009) for a review of this literature. Therefore, teachers'

[42] However, using the LFS we are unable to identify if these second jobs are during term time, or not. Given that teachers, during term time, typically work a 52hr week and are 12% more likely to be dissatisfied with their working hours, compared to the average graduate, it is most likely that the majority of these second jobs are taken out of term time and, therefore, do not impact teacher productivity (Dolton 2004).

higher relative wages could drive the productivity of teachers, and thus pupil outcomes, through the mechanism of feeling more valued.

Theoretical and qualitative studies suggest that salary increases are an important mechanism for motivating and encouraging teachers to work harder (Hanushek et al., 1999, Webb and Valencia 2005). However, other empirical evidence suggests that an unconditional salary increase has no effect on pupils' performance. Most famously De Ree et al., (2015), using data from a randomized experiment in Indonesia, found that doubling teachers' pay had no meaningful effect on students' learning, although it did reduce the likelihood of a teacher holding a second job and improved job satisfaction. Although there is some evidence in the UK that pupils perform better when a teacher's outside option is lower (Britton and Propper 2016), the majority of the literature finds no correlation between changes in teachers' salaries and student outcomes (Hanushek 1986). While the existing evidence suggests that an unconditional pay rise does not impact pupil performance, there is strong evidence that teachers respond positively to performance-related pay in a variety of settings around the world (Atkinson et al., 2009, Kingdon and Teal 2007, Loyalka et al., 2019, Woessmann 2011, Zhang et al., 2019).

An important challenge in all these studies is identifying what teachers' relative wages actually are. In this paper, we use twenty seven years of the Labour Force Survey (LFS) to identify teachers' relative wages using a novel method of estimating teachers' outside option, which takes into account differences in job security, and that entry into teaching is a choice. In doing this we demonstrate that, when we account for non-random selection and differences in job security, teachers' salaries compare favourably to their outside option. One of the main contributions of this paper is that we demonstrate that failing to account for the relative job security of teaching underestimates teachers' relative wages. While the effect in our context is modest (5% for young graduates (under 30's) and between 1 to 2% for older graduates (30 or over)) failing to account for job security could have a large effect on the relative wage estimates for teachers in other settings, such as Spain, where they graduate unemployment rate tends to be higher.

Using the relative wage estimates from the LFS we impute these to five waves of the Trends in International Mathematics and Science Study (TIMSS). Then estimate the effect of relative wages on pupils' test scores and enjoyment of learning by regressing pupil outcomes on teachers' predicted relative wages controlling for a rich set of classroom, school and household level covariates. The effect on pupils' test scores is relatively small, with a 10% increase in teachers' salaries leading to a 0.03sd improvement in test scores, which is similar to the benefit of an additional hour of weekly tuition (Lavy 2015). We also find that teachers' relative wages lead to an increase in their pupils' well-being, measured by enjoyment of learning.

We contribute to the literature on teachers' wages and pupil outcomes in the following ways: first we derive a measure of teachers' relative wages that accounts for differences in job security. This is an important contribution as existing evidence shows that job security plays an important role in the decision to become a teacher and a failure to include this underestimates the returns to teaching (Heinz 2015, Priyadharshini and Robinson-Pant 2003). Second we use a rich data set that allows us to estimate the effect on test scores (Mathematics and Science) and pupil well-being, measured by enjoyment of learning. The existing literature has exclusively focused on the effect of teachers' wages on test scores and other measures of cognitive performance.[43] As teachers play an important role in the development of a wide range of skills, it is important to understand the role teachers' wages have on other skills developed in school.

[43] This is an important finding because empirical evidence from our setting shows that literacy and numeracy skills have a high value in the UK labour market even when we control for education (Vignoles et al., 2011).

The empirical analysis is set in England. This is an important policy setting as the government is currently undergoing a wide range of sweeping policy reforms. The most prominent of which is the commitment to increasing teachers' initial wages to £30,000, an increase of 24%, to attract the highest-achieving graduates into teaching. While making teaching among the highest paid graduate occupations is likely to improve the quality of graduates entering the profession it will take time for new teachers to be recruited, trained and integrate into the education system. This paper shows that policymakers should expect benefits from raising the salaries of existing teachers. This paper is organised as follows; in Section 2 we introduce three methods of estimating teachers outside option and consider if teachers in England are underpaid, in Section 3 we introduce the data on pupil outcomes and the empirical strategy, in Section 4 we present our main results, in Section 5 we present our robustness checks and in Section 6 we discuss our results and conclude.

3.2 Relative Wages

The majority of the literature that investigates the effects that teachers' wages have on pupil outcomes has exploited differences in teachers' wages relative to occupations outside of teaching. This is because using the changes in teachers' absolute wage requires us to assume that all other factors that affect behaviour, such as wages in an alternative occupation, are held constant (Sharir and Weiss 1974). In many settings this assumption does not hold, therefore, many papers that exploit absolute wage differences do not make causal claims. For example, using cross-sectional data Dolton and Marcenaro-Gutierrez (2011) find that countries that pay their teachers higher salaries tend to perform better on international tests. However, there are settings where using absolute wages is appropriate for causal inference. The first is under a large policy intervention where changes in the outside option is likely to be inconsequential. Such a setting includes Indonesia when teachers' salaries were doubled between 2006 and 2015 (De Ree et al., 2015). The second is exploiting wage variations in a setting where non-teachers wages are plausibly similar. As we are not exploiting a significant policy intervention and non-teachers' wages vary in our setting we will exploit variation in teachers' relative wages.

To investigate whether teachers respond to a change in their relative wage in a way that affects their pupils' test scores or well-being, we must first estimate their outside option. The most common measure of estimating how much teachers would have earned had they not gone into teaching is by comparing the earnings of current teachers to the earnings of some non-teaching group. Traditionally, the comparison group used was workers in non-manual occupations (Nickell and Quintini 2002). Although this data is both easily accessible and makes sense in a historic context, these groups are sufficiently different, such that any difference in earnings is likely to be due to differences in workers' characteristics. For this reason, using non-manual occupations is not a sensible approach in our context as it is unlikely to capture teachers' outside option. A comparison group that makes more sense in our context is university graduates. All teachers in England are generally required to have a university degree, meaning that all the occupations available to graduates are, in principle, also available to teachers (Hermann and Diallo 2017). This will be our first measure of teachers' outside option. This will be referred to as "Non-Teachers' Wages (Normal)".

Using this measure consistently finds that teachers earn less than the average graduate.[44] Although this might explain why policymakers struggle to recruit graduates from the higher end of the ability distribution, this does not necessarily mean that teachers could earn more in their outside option. This is due to the fact that selection into teaching is non-random even

[44] The Department for Educations 2019 report uses this method where they state that the earnings gaps between teachers and other graduate professions are "important contributory factors in the recruitment and retention problems facing the teaching profession".

among those with a university degree. Therefore, the average graduates' earnings are unlikely to reflect the salary that teachers would earn if they left teaching.

To get around non-random selection, Chevalier et al., (2007) used a matching strategy to estimate teachers' outside option by comparing teachers' with non-teachers' who looked most like them based on observable characteristics. Using this approach will be our second measure of teachers outside option. This will be referred to as "Non-Teachers' Wages (Matched)".

Using this strategy, Chevalier et al., (2007) they find no evidence to suggest that teachers are underpaid. While these conditional estimates are more likely to reflect teachers outside option it fails to account for another significant benefit of teaching – job security. Existing research shows that job security plays a significant role in the decision to go into teaching, failing to account for this may further underestimate the pecuniary benefits of teaching (Priyadharshini and Robinson-Pant 2003). To estimate teachers' outside option we will modify the matching strategy used by Chevalier et al., (2007) to take this into account. This will be our third measure of teachers outside option and will be referred to as the "Labour Market Returns to Teaching".

We recognize that our matched estimates may still be affected by differences in teaching and non-teaching graduates' unobserved characteristics. One way to get around the difference in unobservable characteristics is to compare the earnings of current teachers to those of former teachers. By doing so, Scafidi et al., (2006) shows that very few teachers who leave teaching enter better-paid occupations. However, this does not tell us how much the average teacher would earn if they quit as attrition is non-random. In the supplementary material, we also estimate teachers outside option by using a matching strategy to compare the wages of current teachers to the earnings of former teachers who look most like them based on observables.[45]

3.2.1 How we estimate teachers' relative wage

Our first method of estimating teachers' relative wages is to compare the average teachers' wage to the average graduates' wage. We use 26 years of the Labour Force Survey (1993 – 2019) and restrict our sample to those who are: university graduates, working age, full time employed and report weekly earnings greater than the expected minimum wage. The average teacher wage, $w_{Teacher}$, is the average weekly wage of all individuals whose main occupation is teaching and who are currently teaching. The average graduate wage is the average wage of non-teaching graduates',$w_{Non-Teacher(Normal)}$. All wages are CPI adjusted to 2019 prices. The difference in the natural log of teachers' and non-teaching graduates' earnings is our first measure of teachers' relative wages. This will be referred to as "Wage Difference (Normal)", as shown in equation 1.

$$Wage\ Difference\ (Normal) = \ Ln\ w_{Teacher} - \ Ln\ w_{Non-Teacher(Normal)} \qquad (1)$$

Table 1 shows the teachers' wage (column a) and graduates' wage (column b) for each year between 1993 and 2019. Although the difference in teachers' and non-teaching graduates' wage might partially explain why policymakers struggle to attract the highest-achieving graduates into teaching, it does not mean that teachers currently face a pay penalty. This is because the composition of individuals who enter teaching have different characteristics to those who do not. For example, using the Destination of Leavers from Higher Education (DLHE), we observe that between 2003 and 2012, 88% of the graduates on initial teacher training programmes were female (vs 56% of graduates not enrolled), 95% were white (vs

[45] Although we will discuss the earnings of teachers who quit teaching we do not necessarily have enough power to use former teachers and our matching strategy so we do not discuss this in detail in the main text but the data is available in the additional material.

85%), 96% state school educated (vs 86%), with only 0.4% from Oxbridge (vs 4%) and 1.7% from Russell Group (vs 26%) institutions.

To account for the differences in observable characteristics, we follow Chevalier et al. (2007) and estimate teachers' outside option by using propensity score matching (PSM). This is our second measure of teachers outside option, $w_{Non-Teacher(Matched)}$. Using this we construct our second measure of teachers' relative wages – "Wage Difference (Matched)", as shown in equation 2.

$$\textit{Wage Difference (Matched):}\ \ Ln\, w_{Teacher} - \ Ln\, w_{Non-Teacher(Matched)} \qquad (2)$$

PSM is a method first proposed by Rosenbaum and Rubin (1983) designed to balance the distribution of baseline covariates between a treatment group (teachers in our case) and a control group (graduates). This strategy allows us to estimate the treatment effect on some outcomes (wages) by comparing the treatment group to members of the control group who look most similar to them on observable characteristics. This is achieved by first estimating the conditional probability of an individual receiving the treatment (i.e. becoming a teacher) given observable characteristics. We do this by regressing observable characteristics on the treatment status using a logistic regression. Then we assign each member of the treatment group to their nearest neighbour in the control group based on their probability of receiving the treatment (propensity score). Within these pairs we use the outcome of the individual in the control group to estimate the counterfactual of the treatment group. Appendix Table 1 shows that teachers are less likely to be men than the graduate population (42% vs 65% in 2000 and 37% vs 59% in 2010) but when we use the matched sample, the difference falls (from 65% to 45% and 59% to 38% respectively). This highlights the importance of controlling for differences in observable characteristics.

For our estimates of teachers' outside option to be unbiased we must have common support (Heckman et al., 1997). Specifically we must compare individuals in the treatment group to individuals who look similar to them in the control group. To test this condition we perform the minima and maxima comparison (Caliendo and Kopeinig 2008) by dropping all observations that have a propensity score which lie outside the minimum and maximum of either the treatment or control group. This has no effect on our estimates. An additional problem with common support can occur if the density in the tails of the distribution is very thin. To test this, we follow Lechner (2004) and do a sensitivity check by replacing the minima and maxima with the tenth smallest and tenth largest observation. Doing this also has no significant effect on our estimates. Therefore, we are confident that our matched estimates are not affected by problems related to common support.

We use PSM to identify the conditional difference in teachers' and non-teachers' salaries because it is simple to estimate, it does not rely on exclusion restriction or functional form to control for differences between teachers and non-teaching graduates, and it is easy to check if covariates are balanced, as shown in Appendix Table 1 (Williamson et al., 2012). We use two alternative strategies (inverse probability weighting (IPW) and regression adjustment (RA)) to estimate teachers outside option as a robustness check. These are presented in figure 1 in the appendix and show that while there are some differences prior to 2000 (when the sample of teachers was roughly 800 each year) from 2001 the estimates are largely similar (roughly 1,500 teachers each year).[46]

Although improved, our second measure does not account for the fact that teaching, as an occupation, has significantly lower unemployment levels. Given that job security plays an important role in attracting graduates into teaching, failing to account for this benefit

[46] IPW is known to perform better when sample sizes are smaller. Our main results are robust to using teachers relative wages estimated via IPW, RA or alternative propensity score matching strategies (i.e. kernel).

underestimates the returns to teaching. We account for this benefit by weighting the teacher and non-teacher wage estimates with a teacher and non-teacher unemployment rate obtained using the LFS. This is our final measure of teachers' relative wages – "Labour Market Returns to Teaching". We estimate this separately using $w_{Non-Teacher(Normal)}$ and $w_{Non-Teacher(Match)}$ in equations 3a and 3b respectively.

Labour Market Returns to Teaching (Normal) = (3a)

$$P(Emp|Teacher, Age, Sex) Ln\, w_{Teacher} + \big(1 - P(Emp|Teacher, Age, Sex)\big) Ln\, w_{JSA} - P(Emp|Non-Teacher, Age, Sex) Ln\, w_{Non-Teacher(Normal)} + (1 - P(Emp|Non-Teacher, Age, Sex)) Ln\, w_{JSA}$$

Labour Market Returns to Teaching (Matched) = (3b)

$$P(Emp|Teacher, Age, Sex) Ln\, w_{Teacher} + \big(1 - P(Emp|Teacher, Age, Sex)\big) Ln\, w_{JSA} - P(Emp|Non-Teacher, Age, Sex) Ln\, w_{Non-Teacher(Match)} + (1 - P(Emp|Non-Teacher, Age, Sex)) Ln\, w_{JSA}$$

Where w_{JSA} is the unemployment benefits they would be eligible for.

The teacher unemployment rate is the sum of unemployed individuals whose last job was teaching divided by the number of teachers plus the quantity of unemployed teachers. While this measure does miss those young people who are unable to find their first teaching job, using the alternative (e.g. individuals who are qualified to teach) would not be any better. A high proportion of young people who finish teacher training decide not to go into teaching (1 in 5 men and 1 in 10 women) and this is driven by preferences and not an inability to find a job (Each year roughly 3,000 more teachers leave the profession than enrol onto teacher training programmes). [47] Using the annual statistics from the Department of Work and Pensions (DWP), we calculate the cost of unemployment by estimating the unemployment benefits (Job Seekers Allowance (JSA)) that everyone would be entitled to given the year,

[47] Specific details about how we use the LFS to calculate teachers' and non-teachers unemployment rate is available in the supplementary material.

their age and sex – similar to the wages we adjust all expected benefit entitlements to 2019 prices using the CPI.

In the following section we will show how teachers' wages compare to non-teaching graduates wages and how accounting for differences in observable characteristics and differences in job security affect our measure of teachers' relative wage.

3.2.2 Comparison across different measures of teachers' relative wages

Comparing the earnings of teachers to non-teaching graduates we find that from 1993 to 2019, the average teacher earns around 13% less than the average graduate (Table 1 column b and figure 1). The difference in pay was largest in the late 1990s but fell to under 10% prior to the 2010 public sector pay freeze. But since then the difference has risen to 14%.

A particularly striking observation is that young teachers' wages are highly competitive and remain this way despite the public sector pay freeze (Figure 2 LHS black solid line vs black dashed line). However teachers' wages do grow at a significantly slower rate than non-teaching graduates wages over the age distribution - teachers in their 30s, 40s and 50s earn around 20%, 23% and 15% less than the average graduate in their respective cohorts (Figure 2 the wedge between the solid and dashed lines grow over the age distribution). This suggests that young people who quit teaching due to pecuniary reasons are motivated by expected future earnings and not current earnings.

Table 1 Teacher and non-teacher annual wages, in pounds, adjusted to 2019 prices using the Consumer Price Index, between 1993 and 2019 using the Labor Force Survey.

	(a)	(b)	(c)	(d)
Year	Teacher Wage	Non-teachers Wage		
		Graduates	Matched	Former Teachers
1993	44000	51400	50500	40500
1994	44100	49300	47100	42000
1995	42400	48900	43400	39800
1996	44700	51400	49500	40800
1997	43300	50500	48800	40400
1998	43000	50900	45200	41700
1999	44300	52100	48500	42000
2000	44300	52800	44300	44800
2001	46500	54400	49000	43600
2002	46800	54600	47400	45100
2003	47600	54800	46100	48800
2004	48200	54300	47200	44300
2005	48500	53900	49000	45200
2006	48400	54200	49100	46100
2007	47400	52900	47000	43700
2008	46700	54700	45000	42800
2009	49100	54000	46800	45700
2010	47900	52000	43500	42000
2011	43700	49700	44500	49000
2012	42500	47900	43200	46500
2013	41400	46700	46600	43000
2014	40600	46800	44000	43200
2015	40400	46700	43100	42800
2016	39600	46900	44100	40200
2017	38700	45500	41400	40000
2018	38300	44100	39900	37200
2019	38100	43800	37500	41200

Note: Wages are all rounded to the nearest hundred. Graduates' wages are the average nominal earnings of all non-teaching graduates. Matched Wages are teachers outside option estimated using nearest neighbour propensity score matching by comparing the earnings of teachers to look most similar to graduates based on observable characteristics. Former teachers' wages are the average nominal earnings of all former teachers who remain employed full time.

Using matching to account for non-random selection, we observe that the average difference in teachers' pay falls from 13% to 3% (table 1 column c). Although there is still evidence that, during the 1990s and after the public sector pay freeze, teachers were paid less than their outside option the magnitude falls significantly (to 9% and 5% respectively). Additionally, the 2019 data suggests that teachers do not, currently, face a wage penalty. However, this may, in part, be due to changes in the composition of the workforce. Teachers' real wages have fallen since 2010 which may have led to the teachers who face a larger pay penalty leaving the occupation at a higher rate – thus changing the composition on both observable and unobservable characteristics. Indeed the proportion of male teachers has fallen (37% in 2010 to 34% in 2018) as has the proportion of teachers with a degree in Mathematical Sciences (14% vs 10%) or Biological Sciences (7% vs 5%).

Accounting for the difference in job security, using our final method has a fairly modest effect (making teaching 1 to 2% more attractive) on our estimates for any group over the age of thirty as older graduates have a very low unemployment rate (under 3% between 1993 and 2019 vs 1.7% for teachers). However, young graduates have a higher unemployment rate (e.g. 5% between 2013 and 2016) and taking this into account does make teaching up to 5% more attractive. The job security young teachers enjoy combined with their relatively high earnings reinforces the notion that young people typically have a significant pecuniary benefit to enter, and remain in, the profession.[48][49]

[48] These figures are not reported.

[49] Although matching accounts for differences in observable characteristics teaching is a vocational occupation. Therefore, these estimates are likely to be biased due to differences in unobservable characteristics. Comparing the earnings of current teachers to the earnings of former teachers, we find no evidence that those who quit teaching entered higher paid occupations between 1993 and 2010. However since the public sector pay freeze, we find that teachers who left the occupation, typically enter occupations that pay up to 9% more than teaching. But this does not mean that current teachers could earn as much as individuals with the highest outside option, ceteris paribus, are more likely to leave e.g. Friedman and Kuznets (1945).

Due to its policy relevance we will briefly discuss how teachers' relative wages differ by school phrase (Primary vs Secondary) and educational background (STEM vs Non-STEM) in the following sections.

3.2.3 Primary and Secondary School Teachers

In this paper, we combine all teachers together (secondary, primary and nursery or special education) so that we can achieve: i) a sample size sufficient to estimate the relative wages by sex and age, and ii) intertemporal consistency – prior to 2001 the LFS does not allow us to identify which type of teacher the respondent is.[50] However, it is still interesting to look at the differences between different categories of teachers (these figures are not reported). For example, comparing the earnings of secondary (primary) school teachers to the earnings of non-teaching graduates between 2001 and 2019, we find that teachers earn between 5-12% (13-23%) less. Although primary and secondary school teachers are on the same national pay scales, it is unsurprising that primary school teachers earn less than secondary school teachers, relative to the average graduate, due to differences in the workforce composition. Teachers' wages are linked to experience and primary school teachers tend to be significantly less experienced (according to the 2018 School Workforce Census 33% (24%) of classroom primary (secondary) school teachers are under 30 while 13% (16%) are over the age of 50).

Using matching to account for non-random selection we find that, prior to the public sector pay freeze, both primary and secondary school teachers' wages were fairly similar to their outside option. While both suffered significant pay penalties due to the pay freeze (up to 8% for secondary and 11% for primary) changes in the composition of the school workforce mean that there is no strong evidence that secondary school teachers face a pay penalty today

[50] From 1993-2000, the LFS's main occupation code does not allow us to identify the type of teaching professional the respondent is.

(the secondary school teachers with the highest outside option left the profession) but the average primary school teacher does face a pay penalty of around 8% today (2019).

3.2.4 Relative Wages of STEM and Non-STEM Teachers

In England, teacher recruitment and retention challenges are more severe in areas that require a degree in a STEM subject (i.e. Science, Technology, Engineering and Mathematics). Given that STEM graduates typically earn more in non-teaching jobs, differences in relative wages could explain this.[51]

Table 2 shows that teachers with a university degree in a STEM subject typically face a wage penalty for entering the teaching profession. However, the magnitude of the penalty has fallen dramatically from over 12% in the mid-90s to around 6% (column a). This suggests that teaching has become more attractive to STEM graduates despite the public sector pay freeze. We also observe that non-STEM graduates are relatively better off in teaching as they typically earn as much in teaching as they would in an outside option, if not more (column b).

Given that STEM teachers have a higher outside option we would expect STEM teachers who leave teaching to enter higher-paid occupations, on average. But we do not have any strong evidence that this is the case (column c). One possible reason for this might be that the skills a teacher acquires are so occupation-specific that they constrain future labour market opportunities. However, we also observe that, since the public sector pay freeze, non-STEM graduates who leave teaching appear to be entering higher paying occupations (10% higher since 2015). While it is possible that teaching might constrain future labour market opportunities differently for STEM and non-STEM graduates, it is possible these graduates

[51] To get a sample that is large enough to estimate teachers' relative wage by degree subject, we combine the two preceding and two following LFS years. For example, for the STEM and Non-STEM wages in 1995 we merge the LFS years 1993-96. Further details are available in the supplementary material.

also have systematically different preferences in the types of jobs they would be interested in outside of teaching.

Table 2 Ratio of teacher and non-teaching wages using our matching strategy and our normal strategy by University Subject Field and years using the LFS.

Years[52]	Strategy	Comparing current teachers to Graduates		Comparing current teachers to qualified teachers who are not teaching	
		(a) STEM	(b) Non-STEM	(c) STEM	(d) Non-STEM
1993-1996	Matching	0.875	0.906	NA	NA
	Normal	0.880	0.872	1.007	1.075
1997-2000	Matching	0.866	0.938	NA	NA
	Normal	0.831	0.869	1.031	1.052
2001-2004	Matching	0.908	1.043	NA	NA
	Normal	0.862	0.887	0.956	1.036
2005-2008	Matching	0.917	1.061	NA	NA
	Normal	0.867	0.911	0.970	1.070
2009-2012	Matching	0.948	1.033	NA	NA
	Normal	0.905	0.922	0.900	0.982
2013-2016	Matching	0.937	0.932	NA	NA
	Normal	0.883	0.869	0.999	0.903

Columns a-b estimate teachers outside option using non-teaching graduates while columns c-d use qualified teachers who are no longer teaching. Columns a and c estimate the outside option for teachers with a degree in a STEM subject and columns b and d estimate it for teachers without a degree in a STEM subject. In columns c and d we are unable to estimate teachers' outside option using propensity score matching using former teachers as our comparison group due to the modest sample size.

[52] To get a sample size large enough to estimate teachers' and non-teachers' wages by degree subject I had to merge 4 years of LFS data together.

3.3 Teacher Pay and Pupil Outcomes

Having derived relative wage measures, we will now estimate the effect of these measures on pupil performance using measures of pupil outcomes from five waves of the Trends in International Mathematics and Science Study (1995, 2003, 2007, 2011 and 2015). Specifically we are interested in pupils' test scores measured by performance in Science and Maths achievement tests and a measure of well-being, here represented by students' self-reported enjoyment of learning.

3.3.1 Empirical Strategy

To estimate the effect on pupil performance (enjoyment of learning), we will perform a least-squares regression of test scores (learning preferences) on relative wages controlling for a set of pupil, class and teacher characteristics. Using test-score (student survey) data from different grades (4 and 8) and subjects (Math and Science), we estimate the following:

$$\mathrm{Y}_{ict} = \beta_0 + \beta_1 wage_{ct} + \beta_2 \boldsymbol{X}_{ict} + \theta_t' + \varepsilon_{ict} \qquad (4)$$

Where Y_{ict} is the test score of students i in class c in year t. The test scores are originally standardized so they have an international mean of 500 and a standard deviation of 100. As we are not using the international dataset, we re-standardize the scores within our sample of English students to have a mean of 0 and a standard deviation of 1 for ease of interpretation. To estimate the effect of relative wages on non-cognitive skills we replace Y_{ict} with a dummy that indicates whether the student i in class c in year t enjoys learning, or not.

Our regressor of interest,$wage_{ct}$,is the difference in the natural log of teachers' and the natural log of non-teachers' wages of the teacher in class c at time t . Where the differences are either the simple difference in earnings or the weighted difference shown in equations 1, 2 and 3 and non-teachers' earnings are estimated using either the average graduates' earnings or matching. $\boldsymbol{X}$ is a vector of controls for pupil, class and teacher background characteristics.

This vector includes the relative student age measured in the difference in months from the median, the students' sex measured as a male dummy, the size of class above the median (by subject). To control for the child's socioeconomic status, we use five dummies to control for the number of books at home (0-10, 11-25, 26-100, 101-200, 200+) a dummy if they have a computer at home and a dummy if they speak English at home. We also control for teacher characteristics, these are: sex, experience (using 5 dummies), and age (using 6 dummies for different age groups.). The last term, θ_t represents year fixed effects. Our coefficient $\beta_1$is our parameter to be estimated. ε_{ict} is our pupil specific error term observed at time t in class c. Our standard errors are clustered at the classroom level because the unobservable component of pupil outcomes in the same class is likely to be correlated (e.g. class resources, time spent on certain topics) and because predicted teachers' pay is constant within classrooms.

The difficulty of interpreting $\beta_1$as a causal effect, in equation 4, is that the variation in teachers' relative wages may not be exogenous to the variation in pupil performance. Indeed there are two forms of selection that could bias our results. The first of these is between school selection, in which students from more affluent households or higher ability, could select into schools that put a lot of emphasis on academic achievement and pay their teachers higher salaries (upward bias). Conversely, we might have situations where schools which have a higher proportion of students from less affluent backgrounds, or lower academic ability, might have to pay a wage premium to attract teachers (downward bias). The second is within school selection, in which more able students might be separated into different classes and taught by more able/higher paid teachers.

Between school selection is potentially an issue in our setting: while teachers' pay scales are determined at the national level, schools have the freedom to pay teachers any amount within the centrally defined minimum and maximum, for a given level of experience. We think that within school selection could also be an issue for the older (grade 8) students in our sample, as most schools in England tend to sort students into classes by ability during secondary school. Whatever the source of endogeneity, it is possible that variation in teachers' wages, $wage_{ct}$, is associated with variation in pupil outcomes, Y_{ict} due to these other reasons and not simply because it affects teachers' productivity. Therefore, using actual teachers' pay would not provide us with a causal effect of teachers' wage on pupil performance.

In the TIMSS data, we do not observe actual teacher wages for each class, i.e. $wage_{ct}$ and are therefore unable to estimate equation 1. Instead, we use the LFS data to obtain a measure of teachers' wages as predicted by a model where we use age, sex and year as explanatory variables. Using these variables, we then impute the estimated wages to the TIMSS data. This way our wage measure changes by class only to the extent that classes are taught by teachers of a different sex and age. Ultimately, what we are exploiting is simply variation in teachers' wages by year, sex and age. Consequently, β_1 is less likely to be affected by a problem of endogeneity and could be interpreted as the causal effect of teachers' relative wages on pupil performance and enjoyment of learning.

Since $wage_{ct}$ is an estimated regressor – relative wages are imputed from the LFS and assigned to teachers based on the teachers' sex, age and the year they are observed - standard errors calculated in the usual way are biased. This is due to the fact that teachers' predicted relative wages has additional sampling variance that needs to be taken into account when we calculate the variance of our final parameter estimates. To obtain unbiased standard errors, we follow Chevalier et al., (2007) and bootstrap the estimates (500 times).

As a robustness check, we exploit variation within schools with a similar level of attainment by using school attainment fixed effects to show that our main results are robust to this more conservative specification. We do not use school attainment fixed effects in our main model because the schools' prior attainment data is not available in the most recent wave (2015) and therefore including this forces us to drop roughly 20% of our sample.

3.3.2 Data

The TIMSS data comes from tests in Science and Mathematics that are administered by the International Association for the Evaluation of Educational Achievement to nationally representative pupils in grades 4 (approximately age 9) and 8 (age 13). TIMSS is an international assessment designed to assess and compare the achievements of young people in more than 60 countries. Along with the tests, TIMSS also contains a rich amount of data on the students, the schools they attend and the teachers who teach them. We merge the pupil performance data with the pupil and teacher surveys together from the 1995, 2003, 2007, 2011 and 2015 TIMSS surveys which gives us our data set.

The TIMSS 4th Grade assessment in England is taken by pupils in Year 5 (primary school) and the 8th Grade assessment is taken by Year 9 pupils (secondary school) as long as the average class age is over 9.5 (13.5) years old at the time of assessment for Grade 4 (Grade 8). However, the 1995 and 2003 TIMSS waves were assigned based on age and not years of schooling. This means that the Grade 8 tests were taken by students in two adjacent grades that contain the largest proportion of 13 year olds (or 10 year olds for Grade 4). In England, this means that the grade 8 tests were taken by Year 8 and Year 9 pupils and the Grade 4 tests by Year 4 and Year 5 pupils. As a consequence the average ages of pupils are moderately lower in these waves.

TIMSS is designed to be nationally representative of pupils. The assessment is randomly assigned to classes using a stratified two-staged cluster sample design. First schools are sampled with probabilities according to their size from the list of all schools in the population that contain eligible students. They are stratified according to demographic characteristics, but the exact variables used differ by country. The most common are: region, urbanization and socioeconomic indicators. The second stage is selecting one or more classes from those eligible within the selected school. Pupils with additional educational needs who are unable to follow the test instructions are excluded, as are students who have received less than one year of instruction in the language of the test. But students who have low prior attainment and/or behaviour problems are eligible to participate. Roughly 2% of children are excluded from the sample in England for one of the reasons above. Conditional on selection and eligibility, participation rates in England are high (96%).

In this paper we drop all pupils where we either cannot match the pupil to a teacher, or where the age and/or sex of the teacher who taught them is missing. We drop these students because we assign teachers' relative wages based on their sex and age –if these are missing, we are unable to assign them a teaching and non-teaching wage. In addition, we drop cases where the student did not complete the home questionnaire, or those who did not complete the questions we use to control for SES. This is because a student's socioeconomic status is an important predictor of cognitive performance.[53] Across the 5 waves we drop 3,245 students in Grade 4 and 4,225 (9,514) students in Grade 8 Math (Science). This leaves us with a sample of 25,346 Grade 4 pupils in both Maths and Science and 15,177 Grade 8 pupils in Math and 17,302 in Science. Table 3 shows that the young people who we drop from our analysis achieve lower scores on the Mathematics and Science assessment, report a lower enjoyment of learning and tend to be marginally younger.

[53] Across the 5 waves only 126 young people who completed the home questionnaire did not complete the questions we use to control for SES. Including these young people in our model using a missing dummy has no impact on our results.

Table 3 Difference in student performance, enjoyment of learning and age and sex of students dropped from our sample using 5 waves of TIMSS.

	(1) Grade 4 Keep	(2) Grade 4 Dropped	(3) Grade 8 Keep	(4) Grade 8 Dropped	(5) Grade 8 Keep	(6) Grade 8 Dropped
			Science		Math	
Math Score	529.12	513.05***			513.89	490.94***
	(90.69)	(94.92)			(81.52)	(88.22)
Science Score	534.54	523.00***	551.41	534.18***		
	(82.59)	(90.10)	(84.33)	(85.13)		
Enjoy Math (Dummy)	0.81	0.64***			0.64	0.66***
	(0.396)	(0.479)			(0.481)	(0.473)
Enjoy Science (Dummy)	0.74	0.63***	0.74	0.71***		
	(0.440)	(0.482)	(0.439)	(0.454)		
Student Age	10.04	10.01***	14.15	14.04***	14.15	13.84***
	(0.469)	(0.518)	(0.381)	(0.505)	(0.389)	(0.595)
Student Male	0.50	0.50	0.51	0.49***	0.50	0.51
	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)
N	25346	3245	17302	9514	15177	4225

Note. Math and Science scores are at the standardized at the TIMSS level with an international mean of 500 and standard deviation of 100. Enjoy Math and Enjoy Science are (dummies where 1 indicates that they enjoy learning or not). Mean coefficients; sd in parentheses, standard errors at the usual levels and indicate statistical significant from the corresponding ‘keep’ column. For example, stars in column 2 indicate that the mean in column two is statistically different from the mean in column 1.:* $p < 0.05$, ** $p < 0.01$, *** $p < 0.0$

3.3.3 Assigning Teachers' Relative Wages

We assign each teacher in TIMSS a teaching and non-teaching wage based on their age, sex and the year they are observed. Our wage estimates are obtained from the LFS (see section 2) by combining the two preceding and two following LFS years to each TIMSS year. For example, we merge the LFS years 1993-1996 and use this sample to estimate the relative wages of teachers observed in the 1995 TIMSS wave (see supplementary material). We assign each teacher the following: a teacher wage, a non-teacher wage estimated using matching and a non-teacher wage estimated not using matching. We also assign each teacher a teacher unemployment rate and a non-teacher (graduate) unemployment rate based on their sex, age and year observed using the LFS. Finally, each teacher is assigned an estimate of the unemployment benefit entitlement (JSA) by applying Department of Work and Pensions (DWP) rules (for a give age, sex and year the JSA entitlement is the same for both teachers and non-teachers).[54]

Using this information we compute each teacher's difference in wages – the natural log of their predicted teacher wage minus the natural log of their predicted non-teacher wage. We do this twice, first using non-teachers' wages estimated using matching and second using the outside option estimated using the average graduate's wages.

Finally, we account for both the differences in job security and the cost of unemployment. It is important to note that all the wages are logged so that the results show the effect of a one percent change in wages or relative wages on pupil performance.

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[54] See the DWP website: https://www.gov.uk/benefits-calculators and https://www.gov.uk/government/collections/dwp-statistical-summaries

Table 4 TIMSS Teachers Wage Descriptive Statistics

	Grade 4		Grade 8			
			Science		Math	
	mean	sd	mean	sd	mean	sd
Ln Teacher Wage	6.316	.249	6.42	.224	6.43	.229
Ln Non Teacher Wage Matched	6.283	.298	6.40	.283	6.42	.283
Ln Non Teacher Wage Graduate	6.384	.298	6.52	.282	6.53	.283
Difference In Wage Matched	.032	.123	.009	.123	.004	.122
Difference in Wage Graduate	-.068	.101	-.104	.105	-.104	.104
Teacher Unemployment Rate	1.710	.438	1.73	.469	1.76	.499
Graduate Unemployment Rate	3.123	1.400	2.94	1.38	2.93	1.40
Labour Market Differences Match	.061	.126	.034	.126	.029	.126
Labour Market Differences Graduate	-.037	.111	-.076	.114	-.077	.113
N	25,346		17,302		15,177	

Note. The estimates for teachers' and non-teachers' wages come from 1993-2019 LFS with all wages adjusted to 2019 prices. Non-teacher Wage graduates is the average non-teaching graduates wage while non-teacher wage matched is non-teaching graduates' wage matched to teachers using nearest neighbour propensity score matching. The difference in wages is Log(Teacher Wage) – Log (Non-Teacher Wage) while the labour market differences is the same but they define *Log(Teacher Wage) as* $P(Emp|Teacher, Age, Sex) Log\ w_{Teacher} + \left(1 - P(Emp|Teacher, Age, Sex)\right) Log\ w_{JSA}$ *and Log (Non-Teacher Wage) as* $P(Emp|Non-Teacher, Age, Sex) Log\ w_{Non-Teacher} + (1 - P(Emp|Non-Teacher, Age, Sex)) Log\ w_{JSA}$.

Table 4 shows the means and standard deviations of these different measures. From this table rows 1, 3 and 5 show that the average graduate earns more than the average teacher but when we account for non-random selection, there is no evidence that the teachers in our sample, on average, face a pay penalty (rows 2 and 4). Additionally, teachers are significantly less likely to be unemployed than graduates (1.7% vs 3.1% for Grade 4 teachers and 1.8% vs 2.9% for Grade 8 teachers). Therefore, when we combine these differences we find that the teachers in our TIMSS Grade 4 and Grade 8 samples do not, on average, face a pecuniary penalty for remaining in the profession.

3.3.4 Descriptive Statistics

Table 5 presents the descriptive statistics for the students who took the TIMSS assessment. Consistent with the design of the assessment, where the average class age for grade 4 (grade 8) had to be higher than 9.5 (13.5), the grade 4 students are typically 10 years old and grade 8 students are 14 years old. There is an equal gender split for both grades.

More grade 8 students live in a household with a home computer (94% vs 87%). Grade 4 pupils are more likely to be taught by a teacher with less than 4 years' experience (27% vs 22.5% for grade 8 Math and 21.4% for Science). The younger pupils are also more likely to be taught by a teacher 25 or under (7.8% vs 6.1% for grade 8 Math and 4.9% for Science) and over 60 (15.4% vs 2.5% Math and 2.1% Science). Consistent with the gender gap in primary teaching the young pupils are much less likely to be taught by a male teacher (26%) than the older pupils where it is a relatively even gender split.

Table 5 TIMSS students descriptive statistics.

	Grade 4		Grade 8			
			Science		Math	
	mean	sd	mean	sd	mean	sd
Student Age	10.040	.469	14.148	.381	14.147	.3893
Student Male	.497	.500	.507	.499	.499	.500
Books at home:						
0-10	.097	.295	.119	.324	.135	.342
11-25	.189	.391	.181	.385	.197	.398
26-100	.320	.466	.286	.452	.286	.452
101-200	.198	.399	.191	.393	.184	.388
200+	.195	.396	.220	.414	.196	.397
Home Computer	.870	.335	.942	.233	.947	.225
Speak English in Home	.781	.414	.868	.337	.873	.332
Class Size Above Median						
Math	.540	.498			.542	.498
Science	.549	.498	.534	.498		
Teacher experience Years:						
1	.092	.289	.078	.269	.078	.268
2	.100	.300	.071	.258	.071	.258
3	.078	.269	.065	.247	.076	.265
4	.076	.252	.063	.244	.053	.224
5	.087	.282	.044	.206	.050	.218
6+	.565	.495	.675	. 468	.670	.470
Techer Age:						
Under 25	.078	.268	.049	.218	.061	.240
25-29	.087	.282	.191	.393	.167	.373
30-39	.086	.280	.300	.458	.270	.444
40-49	.197	.398	.237	.425	.278	.448
50-59	.276	.447	.199	.399	.196	.397
60+	.154	.362	.021	.143	.025	.158
Teacher Male	.261	.439	.495	.499	.497	.500
n	25,346		17,302		15,177	

This table shows the descriptive statistics of the students in our TIMSS sample. For example the final row should the proportion of Grade 4 students who have male teachers (column 1, 26.1%).

Table 6 OLS regression of Grade 4 and 8 pupil performance on observable characteristics in TIMSS.

	1	2	3	4
	Grade 4		Grade 8	
	Math Score	Science Score	Math Score	Science Score
Class Size Above Median	0.123***	0.101**	0.557***	0.271***
	(0.0445)	(0.0401)	(0.0555)	(0.0519)
Relative Student Age	0.0350***	0.0364***	0.0126***	0.0126***
	(0.00230)	(0.00237)	(0.00206)	(0.00187)
Student Male	0.0876***	0.0489***	0.0924***	0.148***
	(0.0155)	(0.0151)	(0.0222)	(0.0169)
books at home 0-10 (Omitted)				
books at home 11-25	0.381***	0.448***	0.361***	0.440***
	(0.0282)	(0.0268)	(0.0266)	(0.0257)
books at home 26-100	0.748***	0.805***	0.705***	0.809***
	(0.0281)	(0.0275)	(0.0320)	(0.0274)
books at home 101-200	0.994***	1.083***	0.961***	1.176***
	(0.0314)	(0.0313)	(0.0382)	(0.0322)
books at home 200+	1.059***	1.246***	1.232***	1.493***
	(0.0342)	(0.0333)	(0.0431)	(0.0329)
Computer in Home	-0.0388+	-0.000321	0.0540	-0.0134
	(0.0263)	(0.0254)	(0.0377)	(0.0314)
Speak English in Home	0.0103	0.150***	-0.106***	0.0371+
	(0.0243)	(0.0238)	(0.0321)	(0.0249)
Teacher Male	0.0180	0.0236	0.00976	0.0514*
	(0.0315)	(0.0291)	(0.0440)	(0.0290)
Teacher Experience 1 Year	-0.0910*	-0.0888**	-0.0398	0.0317
	(0.0465)	(0.0427)	(0.0789)	(0.0657)
Teacher Experience 2 Years	0.0256	0.0148	0.0207	-0.0549
	(0.0591)	(0.0526)	(0.0984)	(0.0665)
Teacher Experience 3 Years	0.0146	0.00716	-0.191**	0.0159
	(0.0542)	(0.0493)	(0.0902)	(0.0618)
Teacher Experience 4 Years	-0.0834+	-0.0709+	0.163	-0.00617
	(0.0511)	(0.0489)	(0.115)	(0.0620)
Teacher Experience 5 Years	-0.0162	0.00698	-0.0427	-0.0878
	(0.0593)	(0.0563)	(0.117)	(0.0702)
Teacher Experience 6+ years (Omitted)				

[continues on next page]

Teacher age Under 25	-0.0752	-0.0689	-0.00211	-0.215***
	(0.0560)	(0.0563)	(0.111)	(0.0769)
Teacher age 25-29	0.0263	0.00820	0.0765	-0.0315
	(0.0470)	(0.0429)	(0.0746)	(0.0508)
Teacher age 30-39	-0.0157	-0.0285	0.0254	-0.00447
	(0.0347)	(0.0338)	(0.0628)	(0.0382)
Teacher Age 40-49 (Omitted)				
Teacher Age 50-59	0.0984**	0.0992**	-0.110+	0.0183
	(0.0414)	(0.0388)	(0.0681)	(0.0449)
Teacher Age 50+	0.412***	0.230	-0.0295	0.114
	(0.154)	(0.168)	(0.164)	(0.107)
Constant	-0.589***	-0.922***	-0.875***	-1.087***
	(0.0658)	(0.0598)	(0.0880)	(0.0749)
N	25346	25366	15177	17302

Our Dependent variables are standardized to have a mean of 0 and a standard deviation of 1. The regressions include year dummies but are not reported. Standard errors are clustered at the class level and the starts indicate statistical significance at the following levels: +p<0.15, *p<0.10, **p<0.05, ***p<0.01.

Table 6 presents the relationship between our controls and outcomes in a multivariate regression that does not include our regressor of interest. First looking at the differences in school and student characteristics, the first row shows that pupils in larger classes tend to do better. Consistent with the literature this suggests that there is non-random sorting in England where pupils who need more individual attention tend to be sorted into smaller classes (Woessmann and West 2002). Similar to the literature, the second row shows that, within cohorts, older students perform better in Math and Science – an increase in age by one month is associated with an increase in pupil performance by 0.03sd for Grade 4 and 0.01sd for Grade 8 (Bedard and Dhuey 2006, Strøm 2004). Consistent with the existing evidence of gender gaps the third row shows that male students tend to outperform female pupils in both Maths and Science and the gap gets larger with age (Contini et al., 2017, Muñoz 2018).

There is a large body of existing literature that demonstrates the strong relationship between socioeconomic status and academic achievement; these include Duncan and Murnane (2011) and Dahl and Lochner (2012). As we do not know parental income, occupation, or highest educational attainment we use two different controls for SES (Rows 4-9). Our first proxy for SES is books at home. Rows 4-8 show that pupil achievement increases with the quantity of books in the home and the achievement gap is steady for both grade 4 and grade 8 pupils. Consistent with Hanushek et al., (2019), who found that the achievement gap has remained fairly constant between 1954 and 2001 in the US, figure 4 shows that the disadvantage gap in Math has remained fairly constant over the last two decades in the UK. But the difference in Science achievement between the most advantaged pupils and the least advantaged pupils fell by 0.4sd. Our second proxy for SES is having a computer in the home, which (as shown in row 9) has no effect on pupil performance.

Row 10 shows that there is a positive relationship between speaking English in the home for Science performance while there is a negative relationship with grade 8 Math performance, this is consistent with existing evidence in England that uses TIMSS (Greany et al., 2016).

The literature on teacher effects consistently shows that teachers have a significant impact on pupil performance. Among the characteristics which are considered important include the teachers' sex, years of teaching experience and age. We do not observe any aggregate effects of teachers' sex on pupil performance apart from Grade 8 Science, in line with the existing literature we also observe that the pupils with the least experienced teachers and the youngest teachers tend to perform worse (rows 12 – 23).

3.4 Estimation Results

The literature has predominately focused on the effect of relative wages on pupil performance therefore we will introduce these results first (Table 7) and then present the results on learning enjoyment (Table 8).

In our data we only observe one teacher for each student. For the young students (grade 4), this is their only teacher. For the older students (grade 8), this is one of many teachers, likely to be of a diverse profile.[55] As a consequence spill-over effects or complementarities could attenuate any wage effects we find for the older students. For example, the benefits that a pupil who is taught by a more effective Science teacher, who is more motivated due to a higher relative wage, might make a positive difference to their Maths score, and vice versa (spill-over effect). Alternatively, having a more effective maths teacher might increase the returns of having a more effective Science teacher (e.g. by improving numeracy skills). As there is evidence that these effects exist in one form or another it will be fairly difficult to

[55] In a scenario where students are taught by equally effective teachers with correlated characteristics (and therefore are estimated to face the same relative wage) this would not be a problem. However, this is unlikely to hold as secondary school teachers are more diverse than primary school teachers (i.e. 50% male teachers in secondary schools vs 26% in primary).

identify a wage effect on secondary school pupils (Bryson and Papps 2016, Kinsler 2016, Sun et al., 2017). Therefore our main focus will be on the results of the primary school pupils. Our estimates for grade 8 pupils are smaller and less precise than our estimates for the younger pupils, which is consistent with spill-over effects, but we cannot assess their magnitude. The results for our secondary school pupils are available in the appendix (Tables 2 - 4).

3.4.1 Teachers and non-Teachers Wages

Column 1 in table 7 shows that, consistent with an efficiency wage model, the effect of teachers' wages on pupil performance in grade 4 Science is positive. An increase in teachers' wages by 10%, which is roughly how much teachers would expect their salaries to increase after acquiring an additional year of experience (for example moving up from the lowest pay band (M1 to M2) on the 2019-20 pay scales), improves pupil performance by 0.024sd. The effect of such an increase in wages is similar to that identified in the literature from a 1 pupil reduction in class size (Krueger (1999) 0.03sd) and a 15% decrease in traffic pollution Heissel et al., (2019) 0.024sd). What these estimates mean in a wider policy context will be discussed in detail in section 6. The effects on Grade 4 Math performance, columns 8 – 10, display a similar pattern although the magnitude is smaller.

3.4.2 The Difference in Relative wages

In the previous section we observe that teachers' wages are positively associated with pupil performance and non-teachers' wages are negatively associated with pupil performance. Therefore, when we take the difference in teachers' and non-teachers' wages we would expect to observe a positive relationship.

Table 7 OLS regression of grade 4 standardized science and math scores in TIMSS on teachers wages

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
				Science							Math			
Log Teacher Wages	0.240	0.417*	0.447+					-0.0801	0.0843	0.129				
	(0.244)	(0.239)	(0.273)					(0.232)	(0.238)	(0.266)				
Log Non-Teacher Wages (Match)		-0.259***							-0.241***					
		(0.0824)							(0.0771)					
Log Non-Teacher Wages (Normal)			-0.208+							-0.209+				
			(0.139)							(0.130)				
Wage Difference (Match)				0.265***							0.235***			
				(0.0799)							(0.0766)			
Wage Difference (Normal)					0.208+							0.209+		
					(0.139)							(0.130)		
Labor Market Returns to Teaching (Match)						0.296***							0.242***	
						(0.0840)							(0.0796)	
Labor Market Returns to Teaching (Norm)							0.259*							0.197+
							(0.142)							(0.132)
Constant	-0.895***	0.810+	0.489	-0.897***	-0.896***	-0.896***	-0.896***	-0.564***	1.025**	0.827	-0.565***	-0.564***	-0.565***	-0.564***
	(0.0304)	(0.545)	(0.925)	(0.0304)	(0.0304)	(0.0304)	(0.0304)	(0.0309)	(0.509)	(0.864)	(0.0309)	(0.0309)	(0.0309)	(0.0309)
N	25346	25346	25346	25346	25346	25346	25346	25346	25346	25346	25346	25346	25346	25346

Our Dependent variables are standardized to have a mean of 0 and a standard deviation of 1. Regression includes all of our controls, these are: Class Size, Class Size Missing Dummy, Student Age above median in months, student sex, books at home, computer in home, speak English at home, teacher sex, teacher experience, teacher age and year fixed effects. Standard Errors in parentheses clustered at the class room level. Signs indicate significance at the following level +p<0.15,* p<0.10,**p<0.05,***p<0.01. Note: standard errors obtained from bootstrap (500)

Regressing pupils' Science performance on the difference in teachers' and our matched non-teachers' wages (table 7 column 4), we find that a 10% increase in teachers' relative wage causes a 0.0265sd increase in pupil attainment, statistically significant at the 1% level. This effect is stronger than using the non-matched outside option (0.0208sd column 5). While this does provide some evidence that our matched estimate might be a better measure of teachers' outside option, than the average graduates' wage, the two estimates are statistically indistinguishable. We observe a similar effect on Math performance, but with a smaller effect size (column 11 – 12).

Our relative wages' estimates are similar to Britton and Propper (2016), in which a 10% increase in teachers' wages, relative to their local labour market, was found to improve pupil performance by 0.02sd, but are significantly smaller than those found by Dolton and Marcenaro-Gutierrez (2011), where a 10% increase in teachers' relative wages improves pupil performance by between 0.1sd and 0.2sd. However, this is what we'd expect as Dolton and Marcenaro-Gutierrez (2011) are unable to distinguish between selection effects - countries that pay teachers' higher salaries attract more productive teachers - and efficiency wage effects.

3.4.3 Labour Market Conditions and Relative wages

Accounting for differences in job security, and the cost of unemployment, using our constructed labour market returns to teaching we find that the coefficients are marginally stronger. Column 6 shows that a 10% increase in the matched labour market returns to teaching causes a 0.03sd increase in Science and 0.024sd in Math (column 13), all statistically significant at the 1% level, while the more general graduates labour market returns (column 7 and 14) show that the effect is 0.026sd and 0.02sd respectively.

The TIMSS assessments are taken between April and June in England. Therefore, our estimates reflect the impact that a more motivated teacher has after 0.8 to 0.9 of an academic year. Therefore, when evaluating the merit of a salary intervention, to improve teacher retention and recruitment, policymakers should also consider the impact on teacher motivation. For example, we estimate that the increase in teachers' pay scales, for the 2020-21 academic year, of 5.5% (the first stage of increasing teachers starting salaries by 24% and more experienced teachers' salaries by 8%) would improve student test scores by roughly 0.016sd in Science and 0.013sd in Math in the first academic year alone, ceteris paribus.

Second our results indicate that, even in the absence of a policy intervention, the fluctuations in teachers' relative wages over the business cycle will impact pupils' test scores. Specifically, during periods of economic downturn (prosperity), pupils will benefit (suffer) from having a more (less) motivated teacher. For example, if the graduate unemployment rate increases by 4% and teachers' salaries rose by 4%, compared to non-teachers, we would expect pupil outcomes to improve by a magnitude quite close to the effect of a 10% increase in teachers' salaries.

3.4.4 Teacher Pay and Pupil Happiness

A change in teacher effort could also affect their pupils' enjoyment of learning. In the TIMSS students survey students are asked about their attitudes towards learning Mathematics and Science. In response to the question 'I enjoy learning' they can respond Agree a lot, Agree a little, Disagree a little or Disagree a lot. Using this data, we create a dummy that indicates if a young person enjoys leaning the subject (Agree a little or Agree a lot) or not (Disagree a little or Disagree a lot). We find 74% of Grade 4 pupils enjoy learnings science and 80% enjoy learning maths.

Table 8 OLS regression of grade 4 students enjoyment of learnings in TIMSS on teachers wages

	1	2	3	4	5	6	7	8
	Grade 4							
	Science				Math			
Wage Difference (Match)	0.169*** (0.0367)				-0.0122 (0.0325)			
Wage Difference (Normal)		0.197*** (0.0612)				0.0285 (0.0553)		
Labor Market Returns to Teaching (Match)			0.182*** (0.0379)				-0.0109 (0.0359)	
Labor Market Returns to Teaching (Norm)				0.215*** (0.0629)				0.0334 (0.0563)
Constant	0.787*** (0.0151)	0.787*** (0.0152)	0.787*** (0.0151)	0.787*** (0.0152)	0.849*** (0.0128)	0.849*** (0.0128)	0.849*** (0.0127)	0.849*** (0.0127)
DP mean	.757	.757	.757	.757	.820	.820	.820	.820
(SD)	(.428)	(.428)	(.428)	(.428)	(.383)	(.383)	(.383)	(.383)
N	24659	24659	24659	24659	24872	24872	24872	24872

Regression includes all of our controls, these are: Class Size, Student Age above median in months, student sex, books at home, computer in home, speak English at home, teacher sex, teacher experience, teacher age and year fixed effects. Standard Errors in parentheses clustered at the classroom level. Signs indicate significance at the following levels +p<0.15,* p<0.10,**p<0.05,***p<0.01. Note: standard errors obtained from bootstrap (500) and our sample size is marginally smaller because 474 pupils (1.8%) did not complete this question.

As the results in table 8 shows, teachers’ relative wages also have an effect on their pupil’s enjoyment of learning. The main effect is on Science enjoyment (column 1-4) where a 10% increase in the matched labour market returns to teaching increases Science enjoyment by 1.8%, statistically significant at the 1% level.

In the student survey, enjoyment of learning is reported in an ordinal form where 1 indicates that pupils enjoy learning this subject the most and 4 indicates pupils who enjoy learning this subject the least. If we use this variable and regress it on the same covariates using an ordinal probit we find that, in line with our previous results, a 10% increase in teachers’ relative wages has a positive effect on Grade 4 pupils enjoying learning Science a lot (1.75%) and has a negative effect on the probability that a Grade 4 pupil does not enjoying learning a lot (-0.85%), all statistically significant at the 10% level (see figure 5).

As the correlation between learning enjoyment and test scores is relatively weak – 0.015 in Science and 0.04 in Math for primary school pupils – it is unlikely that the effect of relative wages on pupil performance is been driven by changes in pupil happiness, and vice versa. A growing body of literature both in England, and abroad, finds that pupils’ enjoyment of learning and well-being at school, while unrelated to test score performance, are strong predictors of future labour market success (Gibbons and Silva 2011, Jackson 2012).Therefore, our estimates suggest that relative wages have a causal effect on two distinct outcomes: pupil happiness and pupil performance.

Table 9 OLS regression of grade 4 Science and Math scores excluding teachers with two or less years experiences in TIMSS on teachers wages

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
				Science							Math			
Log Teacher Wages	0.279	0.536**	0.526*					-0.223	-0.00275	-0.0252				
	(0.267)	(0.272)	(0.310)					(0.259)	(0.264)	(0.291)				
Log Non-Teacher Wages (Match)		-0.344***							-0.297***					
		(0.0994)							(0.0930)					
Log Non-Teacher Wages (Normal)			-0.270*							-0.216+				
			(0.159)							(0.148)				
Wage Difference (Match)				0.351***							0.287***			
				(0.0985)							(0.0921)			
Wage Difference (Normal)					0.277*							0.209		
					(0.159)							(0.148)		
Labor Market Returns to Teaching (Match)						0.386***							0.299***	
						(0.104)							(0.0969)	
Labor Market Returns to Teaching (Norm)							0.332**							0.206
							(0.165)							(0.151)
Constant	-0.903***	1.367**	0.896	-0.906***	-0.905***	-0.906***	-0.904***	-0.570***	1.389**	0.868	-0.572***	-0.571***	-0.572***	-0.570***
	(0.0344)	(0.657)	(1.064)	(0.0344)	(0.0344)	(0.0344)	(0.0344)	(0.0353)	(0.613)	(0.987)	(0.0353)	(0.0353)	(0.0353)	(0.0353)
N	20462	20462	20462	20462	20462	20462	20462	20462	20462	20462	20462	20462	20462	20462

Our Dependent variables are standardized to have a mean of 0 and a standard deviation of 1. Regression includes all of our controls, these are: Class Size, Class Size Missing Dummy, Student Age above median in months, student sex, books at home, computer in home, speak English at home, teacher sex, teacher experience, teacher age and year fixed effects. Signs indicate significance at the following levels. Standard Errors in parentheses. +p<0.15,* p<0.10,**p<0.05,***p<0.01. Note: standard errors obtained from bootstrap (500)

3.5 Robustness Checks

3.5.1 Inexperienced Teachers

Assuming that new teachers have strong teaching preferences – they will exert high effort regardless of the outside option – we can test our results to check if they are being driven by teacher effort. We do this by running our OLS model again but excluding new teachers – those whose effort is unlikely to be responsive to variation in the relative wage. We define new teachers as those who have two years of experience or fewer (Table 9).

Using this smaller sample if our coefficients are larger it would suggest that our results are driven by teachers but if they are smaller, or unchanged, it would suggest that our results are driven through some other channel. Consistent with our predictions, restricting our analysis to those teachers whose effort we would expect to be responsive to changes in relative wages increases our effect sizes by 1% of a standard deviation in both Math and Science performance. For example, column 6 in table 9 shows that our effect on Science performance increases when we remove the least experienced teachers (the effect of a 10% increase in wages increases from 0.029sd to 0 0.038sd).

3.5.2 Academic Attainment Fixed Effects

Ideally we would include region fixed effects in our main model to account for the fact that there are significant regional differences in England that might bias our results. For many countries in TIMSS, such as Australia, Germany and Northern Ireland you could easily do this using the School Strata as the stratification is by region. In England, stratification is done on two levels. The first is by whether the School is just a Primary School or a combined Primary and Secondary school and the second is by the school's prior level of academic attainment. Using the first level we include a dummy for if the school is a Primary School or a combined school. This has no impact on our main results – although Grade 4 pupils in a combined school tend to score .20sd lower in Science and 0.18sd lower in Math.

Apart from 2015, each wave of TIMSS in England is stratified by six levels of the schools' prior level of academic attainment. The prior levels of academic attainment are calculated using key stage 2 results (primary school) and key stage 3 (secondary school). Table 10 shows that pupils in better schools typically achieve higher scores in both Mathematics and Science.[56] For example, students in the best schools typically outperform students from the lowest achieving schools by around one quarter of a standard deviation. Adding academic attainment fixed effects to our model to exploit within year, within similarly achieving schools, variation Table 11 shows that not only do our main results persist, in this more conservative specification, but the effect sizes get marginally larger. Column 3 shows that the effect on Grade 4 Science of a 10% increase in the labour market returns to teaching increases from 0.0296sd to 0.0362sd.

[56] These categories were based on the schools key Stage 2 (KS2) and key stage 3(KS3) results. These are formal assessments that examine young people on the material that they have learnt in years 3 to 6 (ages 6 to 11 (This is KS2)) and year 7 to 9 (ages 11 to 14(KS3)).

Table 10 OLS regression of primary school pupils' Math and Science scores on schools academic attainment levels in TIMSS

	1 Science Score	2 Math Score
Attainment Level 1 (Omitted)		
Attainment Level 2	0.0757+ (0.0488)	0.0610 (0.0495)
Attainment Level 3	0.0873* (0.0484)	0.0541 (0.0470)
Attainment Level 4	0.156*** (0.0540)	0.175*** (0.0524)
Attainment Level 5	0.166*** (0.0516)	0.133*** (0.0468)
Attainment Level 6	0.236*** (0.0548)	0.230*** (0.0559)
_cons	-1.244*** (0.0752)	-0.870*** (0.0756)
N	17951	17951

Our Dependent variables are standardized to have a mean of 0 and a standard deviation of 1. Regression includes all of our controls, these are: Class Size, Student Age above median in months, student sex, books at home, computer in home, speak English at home, teacher sex, teacher experience, teacher age and year fixed effects. Standard Errors in parentheses clustered at the class level and significant is displayed at the usual levels. +p<0.15,* p<0.10,**p<0.05,***p<0.01. Note these attainment categories are not ordered in TIMSS, I ordered and named them based on the pupils' science scores where the category with the lowest scores is 1 and highest is 6. Also note that the sample sizes are slightly smaller as this table excludes the 2015 survey as the prior attainment data is unavailable.

Table 11 OLS regression of Grade 4 Math and Science Scores using schools prior attainment fixed effects in TIMSS on teachers wages								
	1	2	3	4	5	6	7	8
	Science				Math			
Wage Difference (Match)	0.331*** (0.125)				0.255** (0.107)			
Wage Difference (Normal)		0.152 (0.176)				0.0886 (0.167)		
Labor Market Returns to Teaching (Match)			0.362*** (0.124)				0.255** (0.106)	
Labor Market Returns to Teaching (Norm)				0.255+ (0.176)				0.113 (0.167)
constant	-1.198*** (0.0449)	-1.176*** (0.0448)	-1.199*** (0.0449)	-1.180*** (0.0448)	-0.831*** (0.0416)	-0.813*** (0.0415)	-0.830*** (0.0416)	-0.814*** (0.0415)
N	17931	17931	17931	17931	17931	17931	17931	17931

Our Dependent variables are standardized to have a mean of 0 and a standard deviation of 1. Regression includes all of our controls, these are: Class Size, Student Age above median in months, student sex, books at home, computer in home, speak English at home, teacher sex, teacher experience, teacher age and year fixed effects. Standard Errors in parentheses level and significant is displayed at the usual levels. +p<0.15,* p<0.10,**p<0.05,***p<0.01. . Note: standard errors obtained from bootstrap (500). Our sample size is significantly lower using School prior attainment FE's because the prior attainment data is unavailable in the 2015 survey.

3.6. Conclusion

Using a novel estimation strategy this paper shows that when we account for selection bias and relative job security there is no strong evidence that teachers could leave teaching for a higher paying occupation. However, we do find that the growth in male teachers' wages tends to be flatter than what they would expect in their outside option. As a consequence, when we take into account the differences in earnings growth there is a high probability (>50%) that a male teacher could maximise their lifetime earnings by leaving the occupation. This is despite the fact that their initial wages are fairly similar. Looking at the earnings of teachers who quit we find no evidence that they tend to leave teaching for higher paying occupations. This is also true for teachers with a degree in a STEM subject who have fairly strong labour market opportunities. This suggests that either teaching is a strong negative signal on the labour market, teachers are misinformed about their outside option or individuals who leave the occupation are not motivated by pecuniary factors.

Using our wage estimates we find that teachers' wages, consistent with an efficiency wage model, improve pupils' test scores and well-being, measured by enjoyment of learning. To put the size of our effect on pupil performance into a policy perspective the magnitude of a 10% increases in teachers' relative wages has roughly the same effect that Krueger (1999) found for a 1 pupil reduction in class size in Project STAR and Lavy (2015) found for a one hour increase in weekly instructional time using PISA.

These results indicate that current students will benefit from raising teachers' salaries. Specifically, over an academic year more motivated teachers will improve their students' academic attainment and enjoyment of learning. However, this does not mean that an unconditional salary increase is a cost-effective policy instrument to improve pupil performance since it is extremely expensive. A 10% increase in teachers' relative wages is likely to cost an additional £1.3bn per year in primary schools alone.[57] To put the magnitude of the cost into perspective to achieve the same improvement in pupil performance by reducing class sizes in primary schools would cost £232m.[58] A more efficient mechanism to improve pupil performance could be a conditional wage increase. Atkinson et al., (2009) shows that the effect of performance related pay on pupil performance is noticeably stronger than our estimates and is considerably cheaper to implement.

These results suggests that more experienced teachers are more responsive to wage differentials than less experienced teachers. As the government is committed to increasing less experienced teachers' salaries (roughly 24% by 2022) by significantly more than their more experienced colleagues (8%) this might adversely affect teacher effort. Investigating if teachers' wages, relative to other teachers, influences pupil performance and the potential adverse effects of flattering teachers' pay schedule seems like a promising topic for future research.

This paper provides some evidence that teachers' relative wages also affects pupils' well-being. As well-being plays an important role in a wide range of pupil outcomes failing to consider the wider effects of a policy mechanism might lead to a misallocation of resources (Lévy-Garboua et al., 2006). Therefore, investigating the impact of policy mechanisms on a wider range of outcomes and potential dynamic complementarities seems like an important area of future research.

[57] Using the 2018 SWC 172,055 primary school teaches' (mean salary £38,862) and 83,051 primary academy school teachers (mean salary £37,235). Assumed non-teachers' salaries will grow at 3%.

[58] Reducing primary school class sizes from 27 to 26 would require roughly 9,800 additional teachers. Assuming that we can hire this number of teachers at the lowest point of the pay band (£23,720) and there are not additional costs (such as building additional classrooms or hiring additional support staff).

3.7 Figures

Figure 1. Average teachers' Pay between 1993 and 2019 as a ratio of graduates pay

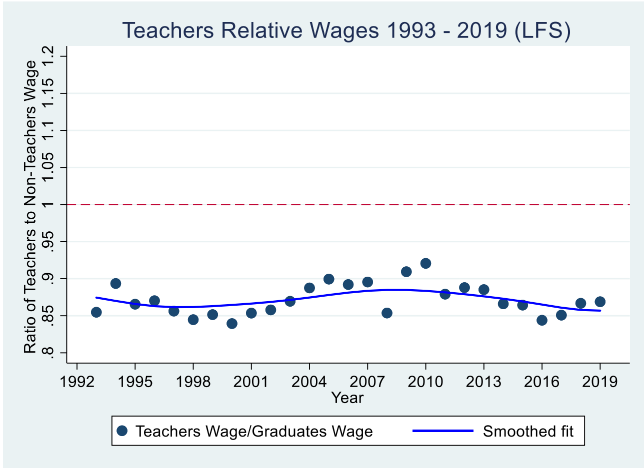
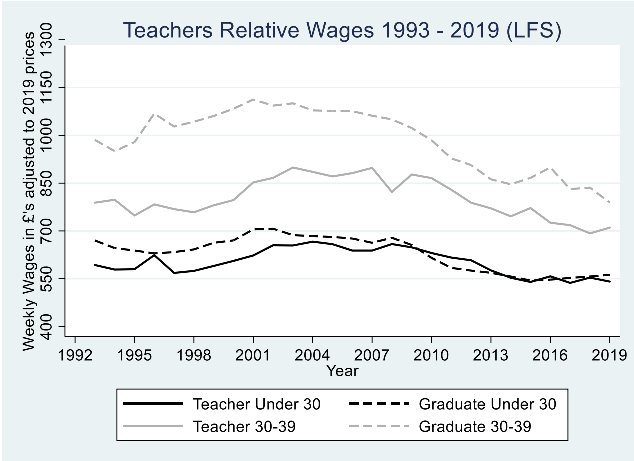


Figure 2 Average teachers' pay between 1993- 2019 as a ratio of graduates pay by age. The LHS is younger teachers and graduates (under 30 and 30-39) and the RHS is older teachers (40-49 and 50-59).



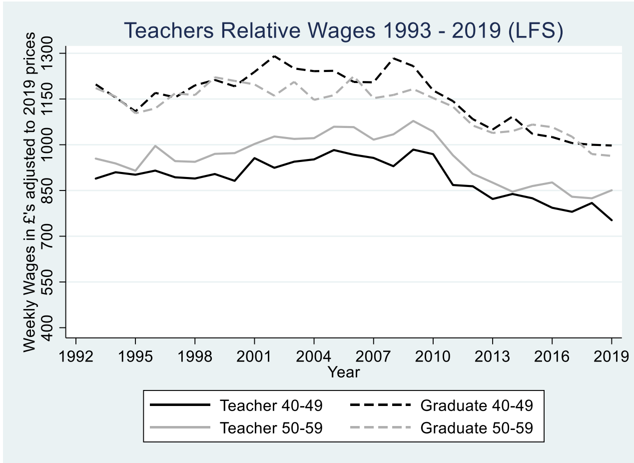
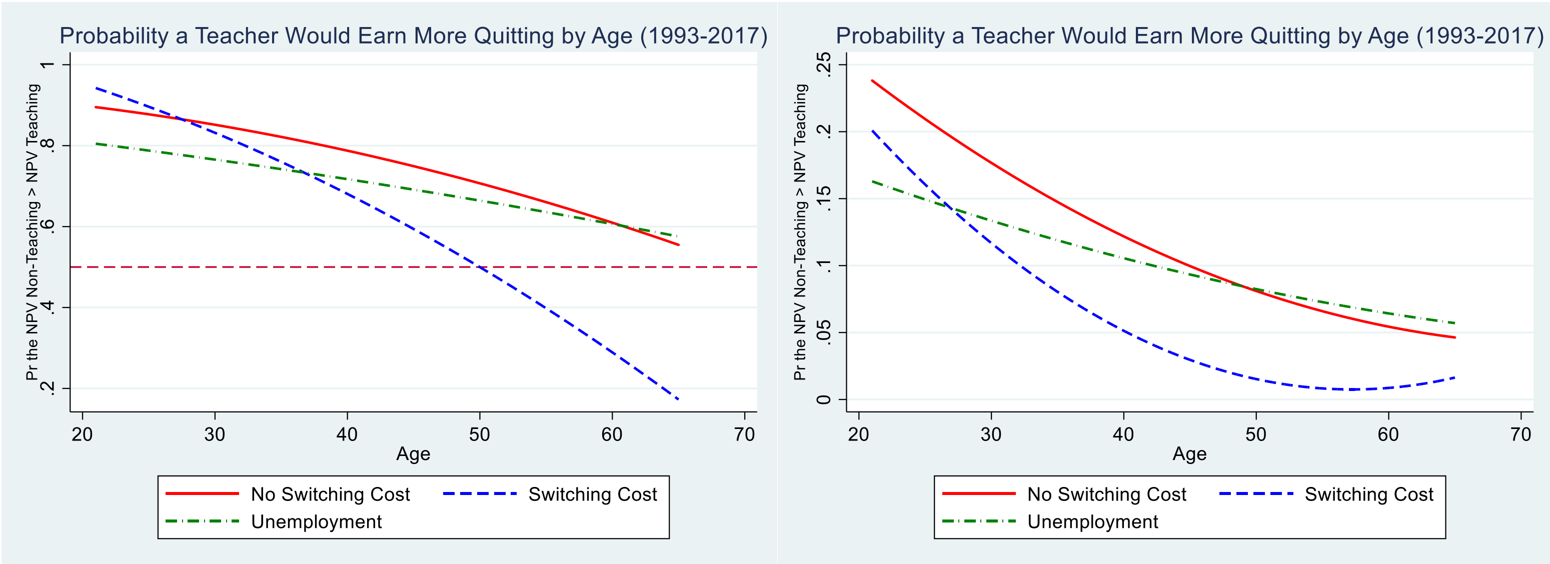
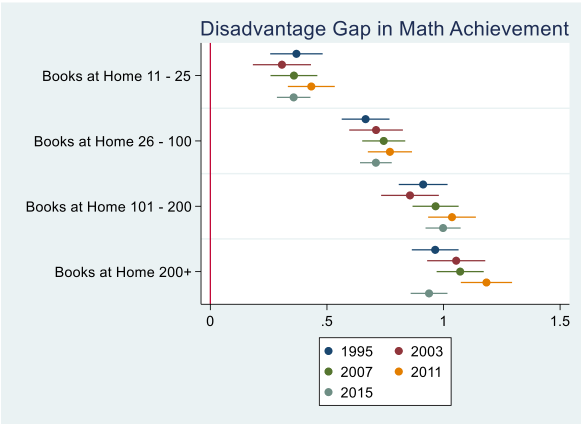


Figure 3 shows the probability that a teacher quitting would maximise their lifetime earnings by age and sex (Male LHS and Female RHS) using the high discounting parameter (25%). The red solid line assumes that markets perfectly clear (i.e. an individual is employed as a teacher or non-teacher with probability 1) and no switching cost. The Blue dashed line assumes that markets perfectly clear but there is a switching cost of 10% (i.e. when teaching sort out of teaching they face an immediate pay penalty). Finally the Green dash dot line is the same as the solid red line but relaxes the assumption about perfect market clearance using the teachers and non-teachers actual unemployment rates from the Labour Force Survey. See the supplementary material for more information.



These figures show clear differences in quitting intentions by male (LHS) and female (RHS) teachers. Even with a high switching cost the probability that a male teacher could maximise their lifetime earnings by leaving the occupation exceeds 50% for the majority of their career while for female teachers the probability is significantly less likely.

Figure 4 shows the change in the difference in achievement by our SES proxy "Books at Home" in Grade 4 Math (LHS) and Science (RHS) achievement in a multivariate regression including all our usual controls. The Omitted variable is 0 – 10 Books at Home.



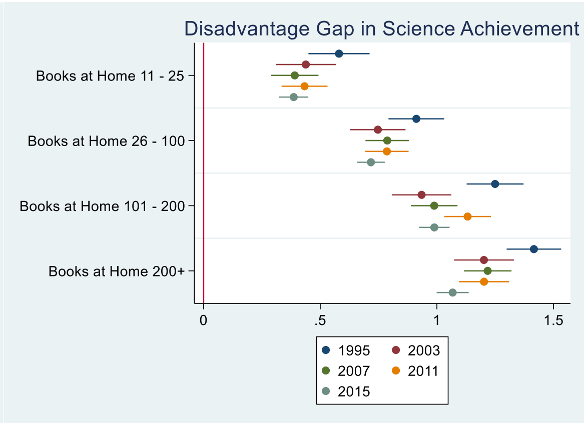
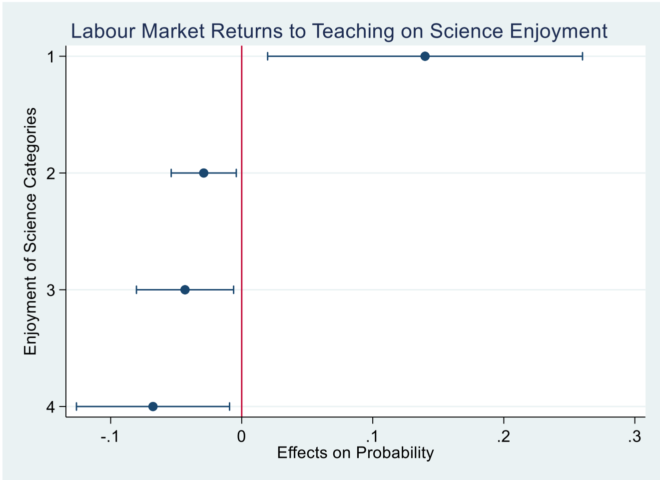


Figure 5 shows the marginal effect of a 1% increase in the labour market returns to teaching on grade 4 science enjoyment where category 1 is enjoy learning the most and category 4 is enjoy learning the least. The confidence intervals are at the 90% level.



Conclusion

In this thesis I explore the importance of pecuniary or labour market factors for educational outcomes and individual educational training choices. The various empirical results obtained can be used to inform the public debate in various areas of educational policy.

Finally, I would like to point out several possible extensions of my work, which I hope to be able to pursue in the future. In my first chapter I find that parents/young people who expect higher labour market returns from a degree also expect a higher probability that their child/they will apply to university. An exciting feature of the data, the Innovation Panel of the UK Household Longitudinal Study, is that I can observe the young person's actual enrolment behaviour. A possible extension of this work would be to investigate whether educational aspirations are predictors of actual behaviour and if the light touch information treatment we administered has any effect on the decision to go to university.

An important policy implication of my second chapter is that an increase in the returns to teaching will only have a meaningful increase on the number of trainee teachers if there is capacity in the system. One important obstacle to increase capacity in the system is that schools are generally reluctant to take on trainee teachers. Unless policymakers incentivise schools to take on trainee teachers capacity constraints mean that it is unlikely that any boost in the 'returns to teaching' will have a transformative effect on the number of graduates enrolling onto teacher training programmes. In the absence of adequate incentives for schools, reducing teacher attrition would be the most fruitful avenue to boosting the supply of teachers in England.

Each year more than 30,000 classroom teachers leave the profession in England. From an unmanageable workload, long hours and unrealistic expectations to a pay scale that doesn't reward experiences, poor leadership quality and a lack of autonomy, there are many, potentially non-exclusive, reasons why a teacher might decide to leave. However existing data does not allow us to distinguish between these factors as a combination of beliefs and constraints can be consistent with observed choices. To address the limitations of traditional data sets I plan to use the mobile EssexLab to elicit teachers' subjective expectations on their probability of remaining in the profession under a variety of different circumstances such as an increase (decrease) in wages, working hours and school leadership quality to identify which factors play the most significant role in determining attrition.

Given the importance of teachers on the development of human capital and the impact of teacher disruptions on pupil outcomes in both the short and long run, understanding the determinants of attrition are beneficial in our context (Hanushek and Rivkin 2006). In addition this research will also contribute to a growing literature that shows that subjective expectations can be used to predict a wide variety of outcomes ranging from voting behaviour (Delavande and Manski 2010) and university enrolment (Delavande and Zafar 2019, Lergetporer et al., 2018) to college major choice (Zafar 2013) and investment behaviour (Hill and Viceisza 2012). Yet one significant area has not been investigated – the decision to leave a job. The extremely high turnover rate in the teaching occupation in England gives me an opportunity to test the hypothesis that economic agents' subjective expectations on their probability of remaining in the profession under different scenarios, over different time horizons, can be used to predict their decision to quit.

Biography

AKERLOF, GEORGE A (1982): "Labor Contracts as Partial Gift Exchange," *The Quarterly Journal of Economics*, 97, 543-569.

ALTONJI, JOSEPH G, LISA B KAHN, and JAMIN D SPEER (2016): "Cashier or Consultant? Entry Labor Market Conditions, Field of Study, and Career Success," *Journal of Labor Economics*, 34, S361-S401.

ANDERS, JAKE (2012): "What's the Link between Household Income and Going to University," *Institute of Education DoQSS Working Paper*.

ARCIDIACONO, PETER (2004): "Ability Sorting and the Returns to College Major," *Journal of Econometrics*, 121, 343-375.

ATKINSON, ADELE, SIMON BURGESS, BRONWYN CROXSON, PAUL GREGG, CAROL PROPPER, HELEN SLATER, and DEBORAH WILSON (2009): "Evaluating the Impact of Performance-Related Pay for Teachers in England," *Labour Economics*, 16, 251-261.

BAERT, STIJN, BART COCKX, and DIETER VERHAEST (2013): "Overeducation at the Start of the Career: Stepping Stone or Trap?," *Labour Economics*, 25, 123-140.

BARR, ANDREW, and SARAH TURNER (2015): "Out of Work and into School: Labor Market Policies and College Enrollment During the Great Recession," *Journal of Public Economics*, 124, 63-73.

BEDARD, KELLY, and ELIZABETH DHUEY (2006): "The Persistence of Early Childhood Maturity: International Evidence of Long-Run Age Effects," *The Quarterly Journal of Economics*, 121, 1437-1472.

BEFFY, MAGALI, DENIS FOUGERE, and ARNAUD MAUREL (2012): "Choosing the Field of Study in Postsecondary Education: Do Expected Earnings Matter?," *Review of Economics and Statistics*, 94, 334-347.

BELFIELD, CHRIS, TEODORA BONEVA, CHRISTOPHER RAUH, and JONATHAN SHAW (2020): "What Drives Enrolment Gaps in Further Education? The Role of Beliefs in Sequential Schooling Decisions," *Economica*, 87, 490-529.

BERGER, MARK C (1988): "Predicted Future Earnings and Choice of College Major," *ILR Review*, 41, 418-429.

BETTS, JULIAN R (1996): "What Do Students Know About Wages? Evidence from a Survey of Undergraduates," *Journal of Human Resources*, 27-56.

BIETENBECK, JAN, MARC PIOPIUNIK, and SIMON WIEDERHOLD (2018): "Africa's Skill Tragedy Does Teachers' Lack of Knowledge Lead to Low Student Performance?," *Journal of Human Resources*, 53, 553-578.

BLEEMER, ZACHARY, and BASIT ZAFAR (2018): "Intended College Attendance: Evidence from an Experiment on College Returns and Costs," *Journal of Public Economics*, 157, 184-211.

BONEVA, TEODORA, and CHRISTOPHER RAUH (2017): "Socio-Economic Gaps in University Enrollment: The Role of Perceived Pecuniary and Non-Pecuniary Returns."

BRITTON, JACK, and CAROL PROPPER (2016): "Teacher Pay and School Productivity: Exploiting Wage Regulation," *Journal of Public Economics*, 133, 75-89.

BRYSON, ALEX, and KERRY L PAPPS (2016): "Spillovers and Team Incentives," Working Paper, University College, London, and University of Bath.

BUCHINSKY, MOSHE, and PHILLIP LESLIE (2010): "Educational Attainment and the Changing Us Wage Structure: Dynamic Implications on Young Individuals' Choices," *Journal of Labor Economics*, 28, 541-594.

CALIENDO, MARCO, and SABINE KOPEINIG (2008): "Some Practical Guidance for the Implementation of Propensity Score Matching," *Journal of economic surveys*, 22, 31-72.

CAMERON, A COLIN, and DOUGLAS L MILLER (2015): "A Practitioner's Guide to Cluster-Robust Inference," *Journal of Human Resources*, 50, 317-372.

CARNEIRO, PEDRO, and JAMES J HECKMAN (2002): "The Evidence on Credit Constraints in Post-Secondary Schooling," *The Economic Journal*, 112, 705-734.

CARRELL, SCOTT E, MARIANNE E PAGE, and JAMES E WEST (2010): "Sex and Science: How Professor Gender Perpetuates the Gender Gap," *The Quarterly Journal of Economics*, 125, 1101-1144.

CASTRO-ZARZUR, ROSA, RICARDO ESPINOZA, and MIGUEL SARZOSA (2019): "Unintended Consequences of Free College: Self-Selection into the Teaching Profession."

CATTANEO, MATIAS D (2010): "Efficient Semiparametric Estimation of Multi-Valued Treatment Effects under Ignorability," *Journal of Econometrics*, 155, 138-154.

CHETTY, RAJ, JOHN N FRIEDMAN, and JONAH E ROCKOFF (2011): "The Long-Term Impacts of Teachers: Teacher Value-Added and Student Outcomes in Adulthood," National Bureau of Economic Research.

CHEVALIER, ARNAUD, and PETER J DOLTON (2004): "The Labour Market for Teachers," Working Paper Series.

CHEVALIER, ARNAUD, PETER DOLTON, and STEVEN MCINTOSH (2007): "Recruiting and Retaining Teachers in the Uk: An Analysis of Graduate Occupation Choice from the 1960s to the 1990s," *Economica*, 74, 69-96.

CIANCIO, ALBERTO, FABRICE KÄMPFEN, ILIANA V KOHLER, DANIEL BENNETT, WÄNDI BRUINE DE BRUIN, JILL DARLING, ARIE KAPTEYN, JÄRGEN MAURER, and HANS-PETER KOHLER (2020): "Know Your Epidemic, Know Your Response: Covid-19 in the United States," *medRxiv*.

CLARK, DAMON (2011): "Do Recessions Keep Students in School? The Impact of Youth Unemployment on Enrolment in Post-Compulsory Education in England," *Economica*, 78, 523-545.

CLOTFELTER, CHARLES, ELIZABETH GLENNIE, HELEN LADD, and JACOB VIGDOR (2008): "Would Higher Salaries Keep Teachers in High-Poverty Schools? Evidence from a Policy Intervention in North Carolina," *Journal of Public Economics*, 92, 1352-1370.

COCKX, BART, and CORINNA GHIRELLI (2016): "Scars of Recessions in a Rigid Labor Market," *Labour Economics*, 41, 162-176.

CONTINI, DALIT, MARIA LAURA DI TOMMASO, and SILVIA MENDOLIA (2017): "The Gender Gap in Mathematics Achievement: Evidence from Italian Data," *Economics of Education Review*, 58, 32-42.

DAHL, GORDON B, and LANCE LOCHNER (2012): "The Impact of Family Income on Child Achievement: Evidence from the Earned Income Tax Credit," *American Economic Review*, 102, 1927-56.

DAVID, H, and DAVID DORN (2013): "The Growth of Low-Skill Service Jobs and the Polarization of the Us Labor Market," *American Economic Review*, 103, 1553-97.

DE REE, JOPPE, KARTHIK MURALIDHARAN, MENNO PRADHAN, and HALSEY ROGERS (2015): "Double for Nothing? Experimental Evidence on the Impact of an Unconditional Teacher Salary Increase on Student Performance in Indonesia," National Bureau of Economic Research.

DEARDEN, LORRAINE, LESLIE MCGRANAHAN, and BARBARA SIANESI (2004): *The Role of Credit Constraints in Educational Choices: Evidence from Ncds and Bcs70. Cee Dp 48*. ERIC.

DEE, THOMAS S (2004): "Teachers, Race, and Student Achievement in a Randomized Experiment," *Review of Economics and Statistics*, 86, 195-210.

— (2005): "A Teacher Like Me: Does Race, Ethnicity, or Gender Matter?," *American Economic Review*, 95, 158-165.

— (2007): "Teachers and the Gender Gaps in Student Achievement," *Journal of Human Resources*, 42, 528-554.

DEL BONO, EMILIA, and GRETA MORANDO (2016): "For Some, Luck Matters More: The Impact of the Great Recession on Early Careers of Graduates from Different Socio-Economic Backgrounds," Working Paper.

DELAVANDE, ADELINE , JOSHUA FULLARD, and BASIT ZAFAR (2018): "Parental Background, Labour Market Expectations and University Applications Intentions in the Uk," *Mimeo.*

DELAVANDE, ADELINE, EMILIA DEL BONO, and ANGUS HOLFORD (2020): "Academic and Non-Academic Investments at University: The Role of Expectations, Preferences and Constraints," *Journal of Econometrics*.

DELAVANDE, ADELINE, EMILIA DEL BONO, ANGUS HOLFORD, and SONKURT SEN (2019): "Skills Accumulation with Malleable Ability: Evidence from a Growth Mindset Intervention."

DELAVANDE, ADELINE, and CHARLES F MANSKI (2010): "Probabilistic Polling and Voting in the 2008 Presidential Election: Evidence from the American Life Panel," *Public opinion quarterly*, 74, 433-459.

DELAVANDE, ADELINE, and BASIT ZAFAR (2014): "University Choice: The Role of Expected Earnings, Non-Pecuniary Outcomes, and Financial Constraints," *FRB of New York Staff Report*.

— (2019): "University Choice: The Role of Expected Earnings, Nonpecuniary Outcomes, and Financial Constraints," *Journal of Political Economy*, 127, 2343-2393.

DOLTON, PETER (2004): "Recruiting High Quality Teachers," *CESifo DICE Report*, 2, 11-20.

DOLTON, PETER J, and KOSTAS G MAVROMARAS (1994): "Intergenerational Occupational Choice Comparisons: The Case of Teachers in the Uk," *The Economic Journal*, 104, 841-863.

DOLTON, PETER, and WILBERT VON DER KLAAUW (1995): "Leaving Teaching in the Uk: A Duration Analysis," *The Economic Journal*, 105, 431-444.

DOLTON, PETER, and OSCAR D MARCENARO-GUTIERREZ (2011): "If You Pay Peanuts Do You Get Monkeys? A Cross-Country Analysis of Teacher Pay and Pupil Performance," *Economic policy*, 26, 5-55.

DOLTON, PETER, ANDREW TREMAYNE, and TSUNG-PING CHUNG (2003): *The Economic Cycle and Teacher Supply*. OECD Paris.

DOLTON, PJ, and W VAN DER KLAAUW (1996): "Teacher Salaries and Teacher Retention, Assessing Educational Practices: The Contribution of Economics," MIT Press, Baumol and Becker (eds).

DUNCAN, GREG J, and RICHARD J MURNANE (2011): *Whither Opportunity?: Rising Inequality, Schools, and Children's Life Chances*. Russell Sage Foundation.

EGALITE, ANNA J, BRIAN KISIDA, and MARCUS A WINTERS (2015): "Representation in the Classroom: The Effect of Own-Race Teachers on Student Achievement," *Economics of Education Review*, 45, 44-52.

EHRENBERG, RONALD G, and DOMINIC J BREWER (1994): "Do School and Teacher Characteristics Matter? Evidence from High School and Beyond," *Economics of Education Review*, 13, 1-17.

EISENHAUER, PHILIPP, JAMES J HECKMAN, and STEFANO MOSSO (2015): "Estimation of Dynamic Discrete Choice Models by Maximum Likelihood and the Simulated Method of Moments," *International Economic Review*, 56, 331-357.

ERMISCH, JOHN, and EMILIA DEL BONO (2012): "Inequality in Achievements During Adolescence."

EVANS, WILLIAM N, ROBERT M SCHWAB, and KATHRYN L WAGNER (2019): "The Great Recession and Public Education," *Education Finance and Policy*, 14, 298-326.

FEHR, ERNST, SIMON GÄCHTER, and GEORG KIRCHSTEIGER (1997): "Reciprocity as a Contract Enforcement Device: Experimental Evidence," *Econometrica: journal of the Econometric Society*, 833-860.

FEHR, ERNST, LORENZ GOETTE, and CHRISTIAN ZEHNDER (2009): "A Behavioral Account of the Labor Market: The Role of Fairness Concerns," *Annu. Rev. Econ.*, 1, 355-384.

FERGUSON, RONALD F (1991): "Paying for Public Education: New Evidence on How and Why Money Matters," *Harv. J. on Legis.*, 28, 465.

FIGLIO, DAVID N (1997): "Teacher Salaries and Teacher Quality," *Economics letters*, 55, 267-271.

FLYER, FREDRICK A (1997): "The Influence of Higher Moments of Earnings Distributions on Career Decisions," *Journal of Labor Economics*, 15, 689-713.

FOOTE, ANDREW, and MICHEL GROSZ (2020): "The Effect of Local Labor Market Downturns on Postsecondary Enrollment and Program Choice," *Education Finance and Policy*, 15, 593-622.

FRIEDMAN, MILTON, and SIMON KUZNETS (1945): *Income from Independent Professional*. New York: National Bureau of Economic Research.

FULLARD, JOSHUA (2019a): "How Much Do You Want It? The Impact of Financial Costs on the Decision to Teach," Work In Progress: Institute for Social and Economic Research.

— (2019b): "Relative Wages and Pupil Performance, Evidence from Timss," Work In Progress: Institute for Social and Economic Research.

— (2020a): "Teacher Supply and Covid-19," https://epi.org.uk/publications-and-research/teacher-supply-and-covid-19/: Education Policy Institute.

— (2020b): "Trends in the Diversity of Teachers in England," https://epi.org.uk/publications-and-research/diversity-of-teachers/: Education Policy Institute.
— (2021a): "The Pandemic and Teacher Attrition: An Exodus Waiting to Happen?," https://epi.org.uk/publications-and-research/the-pandemic-and-teacher-attrition-an-exodus-waiting-to-happen/: Education Policy Institute.
— (2021b): "Teacher Pay Policy: One Size Fits All? ," https://epi.org.uk/publications-and-research/teacher-pay-policy-blog/: Education Policy Institute.
FULLARD, JOSHUA, and JAMES ZUCCOLLO (2021): "Local Pay and Teacher Retention in England."
GERSHENSON, SETH, CASSANDRA HART, JOSHUA HYMAN, CONSTANCE LINDSAY, and NICHOLAS W PAPAGEORGE (2018): "The Long-Run Impacts of Same-Race Teachers," National Bureau of Economic Research.
GERSHENSON, SETH, STEPHEN B HOLT, and NICHOLAS W PAPAGEORGE (2016): "Who Believes in Me? The Effect of Student–Teacher Demographic Match on Teacher Expectations," *Economics of Education Review*, 52, 209-224.
GIBBONS, STEPHEN, and OLMO SILVA (2011): "School Quality, Child Wellbeing and Parents' Satisfaction," *Economics of Education Review*, 30, 312-331.
GILL, TIM (2018): "Preparing Students for University Study: A Statistical Comparison of Different Post-16 Qualifications," *Research Papers in Education*, 33, 301-319.
GOOS, MAARTEN, ALAN MANNING, and ANNA SALOMONS (2014): "Explaining Job Polarization: Routine-Biased Technological Change and Offshoring," *American Economic Review*, 104, 2509-26.
GREANY, TOBY, IAIN BARNES, TAREK MOSTAFA, NICOLA PENSIERO, and CHRISTINA SWENSSON (2016): "Trends in Maths and Science Study (Timss): National Report for England."
GROUP, RUSSELL (2011): "Informed Choices: A Russell Group Guide to Making Decisions About Post-16 Education," Russell Group Cambridge.
HANUSHEK, ERIC A (1986): "The Economics of Schooling: Production and Efficiency in Public Schools," *Journal of economic literature*, 24, 1141-1177.
— (2004): "Some Simple Analytics of School Quality," National Bureau of Economic Research.
— (2011a): "The Economic Value of Higher Teacher Quality," *Economics of Education Review*, 30, 466-479.
— (2011b): "How Much Is a Good Teacher Worth," *Education next*, 11, 40-45.
HANUSHEK, ERIC A, JOHN F KAIN, and STEVEN G RIVKIN (1999): "Do Higher Salaries Buy Better Teachers?," National bureau of economic research.
HANUSHEK, ERIC A, and RICHARD R PACE (1995): "Who Chooses to Teach (and Why)?," *Economics of Education Review*, 14, 101-117.
HANUSHEK, ERIC A, PAUL E PETERSON, LAURA M TALPEY, and LUDGER WOESSMANN (2019): "The Unwavering Ses Achievement Gap: Trends in Us Student Performance," National Bureau of Economic Research.
HANUSHEK, ERIC A, MARC PIOPIUNIK, and SIMON WIEDERHOLD (2014): "The Value of Smarter Teachers: International Evidence on Teacher Cognitive Skills and Student Performance," National Bureau of Economic Research.
HANUSHEK, ERIC A, and STEVEN G RIVKIN (2006): "Teacher Quality," *Handbook of the Economics of Education*, 2, 1051-1078.
— (2007): "Pay, Working Conditions, and Teacher Quality," *The future of children*, 69-86.
HANUSHEK, ERIC A, JENS RUHOSE, and LUDGER WOESSMANN (2015): "Economic Gains for Us States from Educational Reform," National Bureau of Economic Research.
HANUSHEK, ERIC A, and LUDGER WOESSMANN (2011): "How Much Do Educational Outcomes Matter in Oecd Countries?," *Economic policy*, 26, 427-491.
HECKMAN, JAMES J, HIDEHIKO ICHIMURA, and PETRA E TODD (1997): "Matching as an Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Programme," *The Review of Economic Studies*, 64, 605-654.

HEINZ, MANUELA (2015): "Why Choose Teaching? An International Review of Empirical Studies Exploring Student Teachers' Career Motivations and Levels of Commitment to Teaching," *Educational Research and Evaluation*, 21, 258-297.

HEISSEL, JENNIFER, CLAUDIA PERSICO, and DAVID SIMON (2019): "Does Pollution Drive Achievement? The Effect of Traffic Pollution on Academic Performance," National Bureau of Economic Research.

HERMANN, ZOLTÁN (2017): "Does Teacher Gender Matter in Europe? Evidence from Timss Data."

HERMANN, ZOLTÁN, and ALFA DIALLO (2017): "Does Teacher Gender Matter in Europe? Evidence from Timss Data," Budapest Working Papers on the Labour Market.

HIJZEN, ALEXANDER, RICHARD UPWARD, and PETER W WRIGHT (2010): "The Income Losses of Displaced Workers," *Journal of Human Resources*, 45, 243-269.

HILL, RUTH VARGAS, and ANGELINO VICEISZA (2012): "A Field Experiment on the Impact of Weather Shocks and Insurance on Risky Investment," *Experimental Economics*, 15, 341-371.

HOLFORD, ANGUS (2020): "Youth Employment, Academic Performance and Labour Market Outcomes: Production Functions and Policy Effects," *Labour Economics*, 63, 101806.

— (2021): "Access and Returns to Unpaid Graduate Work Experience," *Labour*.

HORVATH, MICHAEL, JOANNE E GOODELL, and VASILIOS D KOSTEAS (2018): "Decisions to Enter and Continue in the Teaching Profession: Evidence from a Sample of Us Secondary Stem Teacher Candidates," *Teaching and Teacher Education*, 71, 57-65.

JACKSON, C KIRABO (2012): "Non-Cognitive Ability, Test Scores, and Teacher Quality: Evidence from 9th Grade Teachers in North Carolina," National Bureau of Economic Research.

JENSEN, ROBERT (2010): "The (Perceived) Returns to Education and the Demand for Schooling," *The Quarterly Journal of Economics*, 125, 515-548.

KAHN, LISA B (2010): "The Long-Term Labor Market Consequences of Graduating from College in a Bad Economy," *Labour Economics*, 17, 303-316.

KINGDON, GEETA GANDHI, and FRANCIS TEAL (2007): "Does Performance Related Pay for Teachers Improve Student Performance? Some Evidence from India," *Economics of Education Review*, 26, 473-486.

KINSLER, JOSH (2016): "Teacher Complementarities in Test Score Production: Evidence from Primary School," *Journal of Labor Economics*, 34, 29-61.

KONDO, AYAKO (2015): "Differential Effects of Graduating During a Recession across Gender and Race," *IZA Journal of Labor Economics*, 4, 1-24.

KONETZKA, R TAMARA, KAREN B LASATER, EDWARD C NORTON, and RACHEL M WERNER (2018): "Are Recessions Good for Staffing in Nursing Homes?," *American journal of health economics*, 4, 411-432.

KRUEGER, ALAN B (1999): "Experimental Estimates of Education Production Functions," *The Quarterly Journal of Economics*, 114, 497-532.

LAVY, VICTOR (2015): "Do Differences in Schools' Instruction Time Explain International Achievement Gaps? Evidence from Developed and Developing Countries," *The Economic Journal*, 125, F397-F424.

LECHNER, MICHAEL (2004): "Sequential Matching Estimation of Dynamic Causal Models."

LERGETPORER, PHILIPP, KATHARINA WERNER, and LUDGER WOESSMANN (2018): "Does Ignorance of Economic Returns and Costs Explain the Educational Aspiration Gap? Evidence from Representative Survey Experiments."

LÉVY-GARBOUA, LOUIS, YOUENN LOHEAC, and BERTRAND FAYOLLE (2006): "Preference Formation, School Dissatisfaction and Risky Behavior of Adolescents," *Journal of Economic Psychology*, 27, 165-183.

LI, DANYAO, MICHAEL R RICHARDS, and COADY WING (2019): "Economic Downturns and Nurse Attachment to Federal Employment," *Health economics*, 28, 808-814.

LINDLEY, JOANNE, and STEPHEN MACHIN (2012): "The Quest for More and More Education: Implications for Social Mobility," *Fiscal Studies*, 33, 265-286.

LOCHNER, LANCE, and ALEXANDER MONGE-NARANJO (2012): "Credit Constraints in Education," *Annu. Rev. Econ.*, 4, 225-256.

LOYALKA, PRASHANT, SEAN SYLVIA, CHENGFANG LIU, JAMES CHU, and YAOJIANG SHI (2019): "Pay by Design: Teacher Performance Pay Design and the Distribution of Student Achievement," *Journal of Labor Economics*, 37, 621-662.

MACHIN, STEPHEN, and ANNA VIGNOLES (2004): "Educational Inequality: The Widening Socio-Economic Gap," *Fiscal Studies*, 25, 107-128.

MALGWI, CHARLES A, MARTHA A HOWE, and PRISCILLA A BURNABY (2005): "Influences on Students' Choice of College Major," *Journal of Education for Business*, 80, 275-282.

MANSKI, CHARLES F (1987): "Academic Ability, Earnings, and the Decision to Become a Teacher: Evidence from the National Longitudinal Study of the High School Class of 1972," in *Public Sector Payrolls*: University of Chicago Press, 291-316.

— (2004): "Measuring Expectations," *Econometrica*, 72, 1329-1376.

MARCENARO-GUTIERREZ, OSCAR, FERNANDO GALINDO-RUEDA, and ANNA VIGNOLES (2007): "Who Actually Goes to University?," *Empirical Economics*, 32, 333-357.

MARCENARO-GUTIERREZ, OSCAR DAVID, and LUIS ALEJANDRO LOPEZ-AGUDO (2020): "Does Teacher Subject Knowledge Contribute to Student Academic Performance in Developing and Least Developed Countries?," *South African Journal of Economics*, 88, 267-297.

MEYER, ANDREW (2013): "Estimating Discount Factors for Public and Private Goods and Testing Competing Discounting Hypotheses," *Journal of Risk and Uncertainty*, 46, 133-173.

MICHAELS, GUY, ASHWINI NATRAJ, and JOHN VAN REENEN (2014): "Has Ict Polarized Skill Demand? Evidence from Eleven Countries over Twenty-Five Years," *Review of Economics and Statistics*, 96, 60-77.

MUÑOZ, JUAN SEBASTIÁN (2018): "The Economics Behind the Math Gender Gap: Colombian Evidence on the Role of Sample Selection," *Journal of Development Economics*, 135, 368-391.

NAGLER, MARKUS, MARC PIOPIUNIK, and MARTIN R WEST (2015): "Weak Markets, Strong Teachers: Recession at Career Start and Teacher Effectiveness," National Bureau of Economic Research.

NICKELL, STEPHEN, and GLENDA QUINTINI (2002): "The Consequences of the Decline in Public Sector Pay in Britain: A Little Bit of Evidence," *The Economic Journal*, 112.

OREOPOULOS, PHILIP, TILL VON WACHTER, and ANDREW HEISZ (2012): "The Short-and Long-Term Career Effects of Graduating in a Recession," *American Economic Journal: Applied Economics*, 4, 1-29.

OYER, PAUL (2006): "Initial Labor Market Conditions and Long-Term Outcomes for Economists," *Journal of Economic Perspectives*, 20, 143-160.

PAVESE, CATERINA, and ENRICO RUBOLINO (2021): "Do Fiscal Restraints Harm Test Scores? Evidence from Italy," *University Ca'Foscari of Venice, Dept. of Economics Research Paper Series No*, 2.

PRIYADHARSHINI, ESTHER, and ANNA ROBINSON-PANT (2003): "The Attractions of Teaching: An Investigation into Why People Change Careers to Teach," *Journal of Education for Teaching*, 29, 95-112.

RICKMAN, BILL D, and CARL D PARKER (1990): "Alternative Wages and Teacher Mobility: A Human Capital Approach," *Economics of Education Review*, 9, 73-79.

RIVKIN, STEVEN G, ERIC A HANUSHEK, and JOHN F KAIN (2005): "Teachers, Schools, and Academic Achievement," *Econometrica*, 73, 417-458.

RODEIRO, CARMEN L VIDAL (2007): "A Level Subject Choice in England: Patterns of Uptake and Factors Affecting Subject Preferences," *Cambridge: Cambridge Assessment*.

ROODMAN, DAVID, MORTEN ØRREGAARD NIELSEN, JAMES G MACKINNON, and MATTHEW D WEBB (2019): "Fast and Wild: Bootstrap Inference in Stata Using Boottest," *The Stata Journal*, 19, 4-60.

ROSENBAUM, PAUL R, and DONALD B RUBIN (1983): "The Central Role of the Propensity Score in Observational Studies for Causal Effects," *Biometrika*, 70, 41-55.

RUBOLINO, ENRICO (2019): "The Efficiency and Distributive Effects of Local Taxes: Evidence from Italian Municipalities," *Institute for Social and Economic Research„„ISER Working Paper Series*, 2.

— (2020): "Tax Enforcement, Public Spending and Tax Rates: Evidence from the Ghost Buildings Program," *Public Spending and Tax Rates: Evidence From the Ghost Buildings Program (August 6, 2020)*.

— (2021): "Taxing the Gender Gap: Labor Market Effects of a Payroll Tax Cut for Women in Italy."

RUBOLINO, ENRICO, and DANIEL WALDENSTRÖM (2020): "Tax Progressivity and Top Incomes Evidence from Tax Reforms," *The Journal of Economic Inequality*, 18, 261-289.

SCAFIDI, BENJAMIN, DAVID L SJOQUIST, and TODD R STINEBRICKNER (2006): "Do Teachers Really Leave for Higher Paying Jobs in Alternative Occupations?," *Advances in Economic Analysis & Policy*, 6.

SHAPIRO, CARL, and JOSEPH E STIGLITZ (1984): "Equilibrium Unemployment as a Worker Discipline Device," *The American Economic Review*, 74, 433-444.

SHARIR, SHMUEL, and YORAM WEISS (1974): "The Role of Absolute and Relative Wage Differentials in the Choice of a Work Activity," *Journal of Political Economy*, 82, 1269-1275.

SHVARTSMAN, ELENA (2018): "The State of the Economy at Graduation, Wages, and Catch-up Paths: Evidence from Switzerland."

SMITHERS, ALAN, and PAMELA ROBINSON (2003): "Factors Affecting Teachers' Decisions to Leave the Profession."

STINEBRICKNER, TODD R (1998): "An Empirical Investigation of Teacher Attrition," *Economics of Education Review*, 17, 127-136.

STRØM, BJARNE (2004): "Student Achievement and Birthday Effects," *Unpublished manuscript, Norwegian University of Science and Technology*.

SUN, MIN, SUSANNA LOEB, and JASON A GRISSOM (2017): "Building Teacher Teams: Evidence of Positive Spillovers from More Effective Colleagues," *Educational Evaluation and Policy Analysis*, 39, 104-125.

TUCKETT, SAM, DAVID ROBINSON, and FELIX BUNTING (2021): "Measuring the Disadvantage Gap in 16-19 Education."

VAN DEN BERGE, WILJAN, and ARNE BROUWERS (2017): "A Lost Generation? The Early Career Effects of Graduating During a Recession," CPB Netherlands Bureau for Economic Policy Analysis.

VIGNOLES, ANNA, AUGUSTIN DE COULON, and OSCAR MARCENARO-GUTIERREZ (2011): "The Value of Basic Skills in the British Labour Market," *Oxford Economic Papers*, 63, 27-48.

VIGNOLES, ANNA F, and NATTAVUDH POWDTHAVEE (2009): "The Socioeconomic Gap in University Dropouts," *The BE journal of economic analysis & policy*, 9.

WEBB, RICHARD, and SOFÍA VALENCIA (2005): "Human Resources in Public Health and Education in Peru," *An Opportunity for a Different*, 697.

WILLIAMSON, ELIZABETH, RUTH MORLEY, ALAN LUCAS, and JAMES CARPENTER (2012): "Propensity Scores: From Naive Enthusiasm to Intuitive Understanding," *Statistical methods in medical research*, 21, 273-293.

WILLIS, ROBERT J, and SHERWIN ROSEN (1979): "Education and Self-Selection," *Journal of Political Economy*, 87, S7-S36.

WISWALL, MATTHEW (2013): "The Dynamics of Teacher Quality," *Journal of Public Economics*, 100, 61-78.

WISWALL, MATTHEW, and BASIT ZAFAR (2015a): "Determinants of College Major Choice: Identification Using an Information Experiment," *The Review of Economic Studies*, 82, 791-824.

— (2015b): "How Do College Students Respond to Public Information About Earnings?," *Journal of Human Capital*, 9, 117-169.

WOESSMANN, LUDGER (2011): "Cross-Country Evidence on Teacher Performance Pay," *Economics of Education Review*, 30, 404-418.

— (2016): "The Economic Case for Education," *Education economics*, 24, 3-32.

WOESSMANN, LUDGER, and MARTIN R WEST (2002): "Class-Size Effects in School Systems around the World: Evidence from between-Grade Variation in Timss," Institute for the Study of Labor (IZA).

ZABALZA, ANTONI, PHILIP TURNBULL, and GARETH WILLIAMS (1979): *The Economics of Teacher Supply*. Cambridge University Press.

ZAFAR, BASIT (2013): "College Major Choice and the Gender Gap," *Journal of Human Resources*, 48, 545-595.

ZHANG, JIAN, SONGQING JIN, and WEI SI (2019): "Incentivising Teachers? Evaluating the Incentive Effect of China's Teacher Performance-Based Compensation Reform in Rural China," *Australian Journal of Agricultural and Resource Economics*.

Data Biography

Department for Education. (2019) *School Workforce Census 2013 to 2018* https://www.gov.uk/government/collections/statistics-school-workforce

HESA: Higher Education Statistics Agency. (2004). *Destinations of Leavers from Higher Education in the United Kingdom for the academic year 2002-03, and years to 2011-12*. Statistical First Release numbers 77 (2002/03), 89, 101, 112, 124, 137, 148, 162, 178,and 192 (2011/12). 2002/03 data is here:https://www.hesa.ac.uk/news/08-10-2004/sfr77-destinations-of-leavers.

HESA: Higher Education Statistics Agency. (2010). *Introduction - Destination of Leavers Longitudinal Survey 2008-09, 2006-07 and 2004-2005*. Introductions to Destination of Leavers Longitudinal Surveys. 2008-09 data is here:https://www.hesa.ac.uk/data-and-analysis/publications/long-destinations-2008-09/introduction.

IEA. (2019) *Trends in International Mathematics and Science Study, waves 1995, 2003, 2007, 2011 and 2015*
https://timssandpirls.bc.edu/timss-landing.html

Office for National Statistics. (2019) *Labour Force Survey, years 1993 – 2019*. SN 2000026 beta.ukdataservice.ac.uk/datacatalogue/series/series?id=2000026

University of Essex, Institute for Social and Economic Research. (2019). *Understanding Society: Innovation Panel, Waves 1-11, 2008-2018*. [data collection]. *9th Edition.* UK Data Service. SN: 6849, http://doi.org/10.5255/UKDA-SN-6849-12

Appendix Chapter 1

A1 Complete list of expectations questions asked in Waves 8 and 9:

Next we have a few questions about your [son/daughter] [CHILD NAME]'s education plans. On a scale from 0% to 100% where 0% means 'No chance of happening' and 100% means 'Totally likely to happen', please tell me how likely it is that the following events will happen to [CHILD NAME] in the future.

How likely is it that [CHILD NAME] will have a university degree by age 30?

How likely is it that [CHILD NAME] will gain the required qualifications to get into university?

Suppose [CHILD NAME] gains the required qualifications to apply to university. How likely is it that [CHILD NAME] will apply to university?

Suppose [CHILD NAME] gains the required qualifications to apply to university. How likely is it that [CHILD NAME] will apply to university if all costs (tuition, books, boarding, etc) were paid out of a scholarship, grant, bursary or fee reduction scheme?

Excluding any scholarship, grant, bursary or fee reduction scheme that [CHILD NAME] might receive, how much do you expect [CHILD NAME] to pay as yearly tuition if he/she goes to university

How much does [CHILD NAME] expect to borrow yearly in student loans if he/she goes to university

Suppose [CHILD NAME] gains the required qualifications to apply to university, applies, and gets a place. How likely is it that [CHILD NAME] will finish his/her studies?

How likely is it that [CHILD NAME] will be working at age 30 if he/she has a university degree?

How likely is that [CHILD NAME]will be working at age 30 if [CHILD NAME] does not go to university at all?

Look ahead to when [CHILD NAME] will be 30 years old and suppose that he/she is working then. Think about the kinds of jobs that will be available to [CHILD NAME]. Assuming that one pound today is worth the same as one pound when [CHILD NAME] is 30 years old, if he/she had a university degree, how much do you think [CHILD NAME]could earn per year on average at the age of 30

And how much do you think [CHILD NAME] could earn per year on average at the age of 45 if he/she had a university degree?

Which of these do you think might fairly represent [CHILD NAME]'s yearly earnings at age 45 if he/she had a university degree?

Look ahead to when [CHILD NAME]will be 30 years old and suppose that he/she is working then. Think about the kinds of jobs that will be available to [CHILD NAME]. Assuming that one pound today is worth the same as one pound when [CHILD NAME] is 30 years old, how much do you think [CHILD NAME] could earn per year on average at the age of 30 if he/she did not go to university at all?

And how much do you think [CHILD NAME] could earn per year on average at the age of 45 if he/she did not go to university at all?

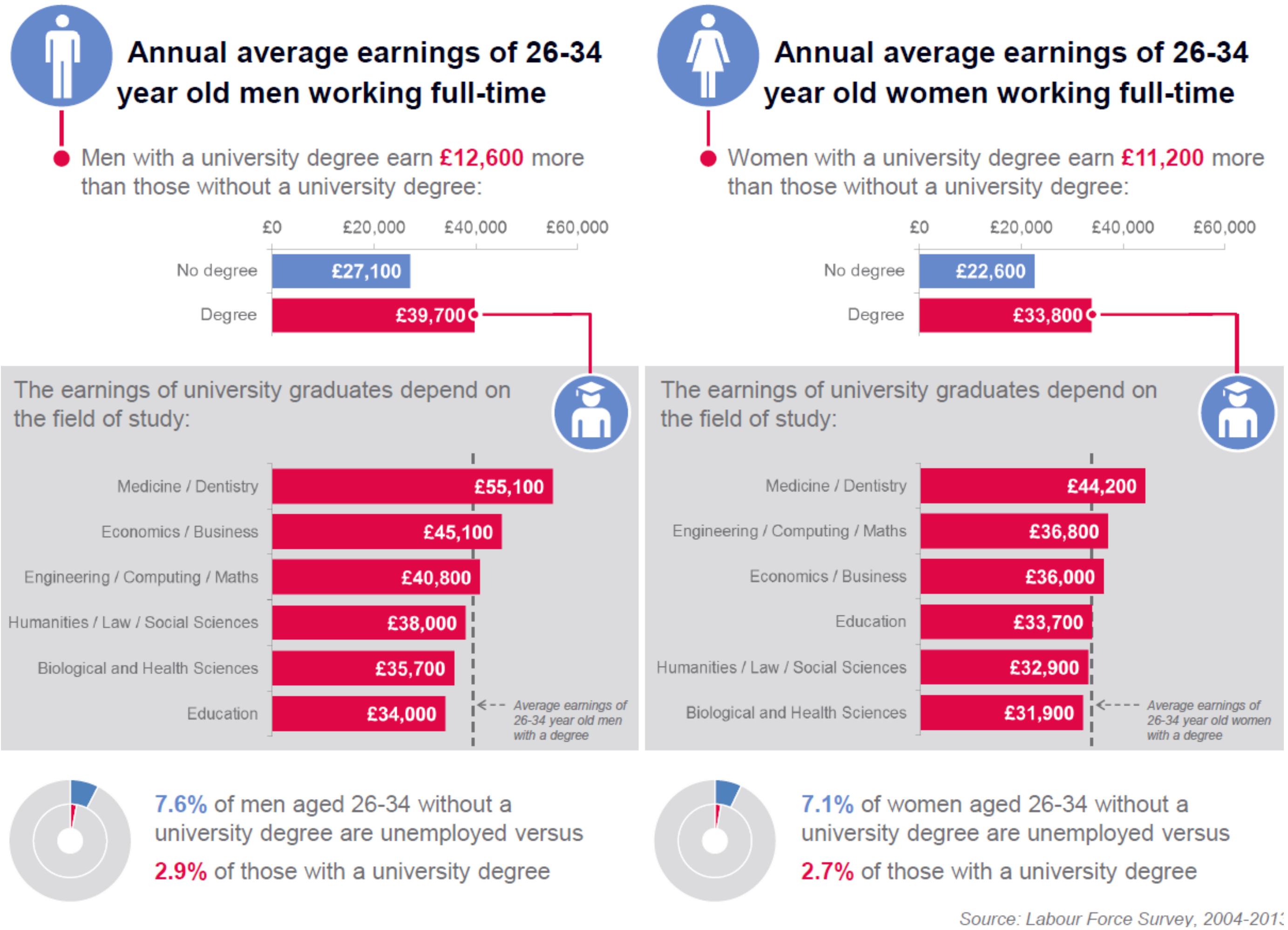
Think about all current 30 year old women / men who are working full time. What is the average amount that you believe these workers currently earn per year if they have a university degree?

What is the average amount that you believe all 30 year old Women / men currently earn per year if they did not go to university at all?

Note that for all the earnings expectations, the following follow-up question was asked if the respondent initially said ‘Don’t know’:

Which of these do you think fairly represents the annual earnings
The response options are bracketed incomes that start at £10,000 p.a. and increase by £5,000 incrementally with the largest value being £100,000 p.a. These secondary responses were combined with the initial responses via bracketed means. The proportion of “don’t knows” varies between 9% and 11%.

Appendix A2. Information Treatment provided to households in-between IP waves 8 and 9.



Appendix table A1. Difference in parent's belief in the employment rate and the actual employment rate

		(1a)	(1b)	(2a)	(2b)	(3a)	(3b)
		Sample		Belief About Women		Belief About Men	
		Belief Difference	Percent Error (Belief)/(Truth) * 100	Belief Difference	Percent Error (Belief)/(Truth) * 100	Belief Difference	Percent Error (Belief)/(Truth) * 100
With A	Mean	5.60	17.42	4.93	17.65	6.19	17.24
degree	(SD)	(14.80)	(17.41)	(13.82)	(16.08)	(15.64)	(18.46)
Absolute	Mean	8.94	17.42	8.50	17.65	9.34	17.24
Value	(SD)	(13.04)	(17.41)	(11.94)	(16.08)	(13.98)	(18.46)
Without A	Mean	5.64	26.00	4.18	23.94	6.93	27.54
degree	(SD)	(21.39)	(25.23)	(20.11)	(25.48)	(22.44)	(25.11)
Absolute	Mean	14.03	26.00	12.44	23.94	15.42	27.54
Value	(SD)	(17.09)	(25.23)	(16.31)	(25.48)	(17.68)	(25.11)
Returns to	Mean	3.22	69.31	2.08	52.03	4.23	84.60
A Degree	(SD)	(13.42)	(290.64)	(10.83)	(270.65)	(15.32)	(306.47)
Absolute	Mean	5.56	120.76	4.03 *	100.81	6.92	138.42
Value	(SD)	(12.63)	(272.68)	(10.26)	(256.39)	(14.30)	(286.07)

Beliefs in 1a , 2a and 3a are all in £10,000's. The others are percentages. T-tests conducted for equality of means between columns 2a and 3a and 2b and 3b. ***,**,* indicate significance at the 1,5 and 10 % levels.

Appendix Table A2 showing parents applications Intentions on their expected returns and observable characteristics by the child's sex (OLS subsample analysis)

	(1)	(2)	(3)	(4)	(5)	(6)
	Probability to Apply to University					
	Male Child			Female Child		
Earnings Returns Aged 30	1.767***			0.471		
	(0.539)			(0.710)		
Labor Market Returns age 30 of going to University		2.835*			2.655	
		(.433)			(2.284)	
Employment Returns			0.286*			0.240
			(0.171)			(0.251)
Child Over 15	-0.783	3.305	-1.004	5.758	7.701	9.360
	(5.373)	(5.025)	(5.614)	(5.963)	(5.714)	(5.974)
Parent Over 45	5.059	7.454	6.287	-0.0695	1.692	-0.480
	(5.584)	(5.239)	(5.839)	(5.906)	(5.539)	(5.916)
Male Parent	-7.596	-10.34**	-3.627	5.378	-0.0439	5.937
	(5.269)	(4.863)	(5.518)	(5.618)	(5.406)	(5.740)
HH Degree	6.167	4.075	9.862*	6.163	1.717	5.384
	(5.520)	(5.016)	(5.516)	(6.646)	(6.603)	(6.330)
Parents Married	13.40**	4.839	6.687	0.202	1.259	-5.007
	(6.394)	(6.038)	(6.018)	(7.399)	(6.812)	(7.240)
HH High Income	-8.236	0.768	-0.973	3.168	4.477	7.469
	(5.898)	(5.742)	(5.791)	(6.371)	(6.043)	(6.116)
White British	-6.359	-3.626	-8.67	13.016	16.57*	11.51
	(5.963)	(5.472)	(6.335)	(9.267)	(8.364)	(8.640)
Ethnic Other	11.45	9.311	1.790	7.02	17.31	9.817
	(10.68)	(9.661)	(9.88)	(12.05)	(11.92)	(11.63)
England	4.356	0.0278	-2.931	-9.407	-13.32	-0.692
	(8.855)	(8.729)	(9.545)	(9.640)	(9.548)	(9.431)
Expected Tuition	-0.0680	-0.549	-0.0984	0.114	0.0383	-0.0794
	(0.763)	(0.700)	(0.794)	(0.617)	(0.574)	(0.639)
Tuition Missing	-11.66	-0.00508	-13.55	-13.45*	-5.696	-12.23
	(8.578)	(8.573)	(8.965)	(7.627)	(7.568)	(7.732)
Constant	60.02***	76.32***	78.01***	72.52***	69.33***	62.14***
	(11.16)	(9.622)	(12.68)	(14.48)	(13.20)	(13.44)
N	120	110	130	106	94	110

The reference category for ethnicity is ethnicity missing. se in parentheses, starts indicate significance as the following labels

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the household level.

Appendix A3 OLS Treatment effect on the Children's accuracy of the distribution of earnings (OLS)

	(1)	(2)	(3)
	Within 10% of the True Value		
	With A Degree	With No Degree	Returns to A Degree
Treatment	0.0202	-0.00324	0.0551
	(0.0875)	(0.1000)	(0.0385)
Accurate at Wave 8	0.110	-0.0459	-0.122^{*}
	(0.130)	(0.141)	(0.0676)
Male Child	0.107	0.352^{***}	-0.0389
	(0.0930)	(0.106)	(0.0610)
HH High Income	-0.118	-0.0892	0.00428
	(0.124)	(0.130)	(0.0372)
HH Degree	0.000936	0.0620	0.130^{*}
	(0.0989)	(0.126)	(0.0755)
England	-0.250	0.0375	0.0711
	(0.214)	(0.0995)	(0.0777)
Ethnic British	0.0251	-0.217	0.141
	(0.116)	(0.132)	(0.188)
Ethnic Other	-0.0367	-0.203	0.0831
	(0.192)	(0.180)	(0.202)
Parents Married	-0.00873	-0.00401	-0.0838
	(0.135)	(0.165)	(0.0764)
Parents Married Missing	-0.0970	-0.285	0.209
	(0.156)	(0.172)	(0.200)
Constant	0.319	0.0478	-0.196
	(0.259)	(0.180)	(0.257)
N	65	65	64

Standard errors in parentheses, starts indicate significance as the following labels * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
We use robust standard errors. Ethnicity Missing is our reference category for our ethnicity variables.

Appendix Chapter 2

Appendix Table A1 Tuition Fees Schedule and Professional Skills Pass Threshold by year of entry

Year Started Undergrad	Year Started Postgrad[+]	Undergraduate Fees	PGCE Fees	Professional Skills Test
1998	2001	£1,000	£1,000	Low
1999	2002	£1,000	£1,000	Low
2000	2003	£1,000	£1,000	Low
2001	2004	£1,000	£1,000	Low
2002	2005	£1,000	£1,000	Low
2003	2006	£1,000	£3,000	Low
2004	2007	£1,000	£3,000	Low
2005	2008	£1,000	£3,000	Low
2006	2009	£3,000	£3,000	Low
2007	2010	£3,000	£3,000	Low
2008	2011	£3,000	£3,000	Low
2009	2012	£3,000	£9,000	Low
2010	2013	£3,000	£9,000	High
2011	2014	£3,000	£9,000	High
2012	2015	£9,000	£9,000	High
2013	2016	£9,000	£9,000	High
2014	2017	£9,000	£9,000	High
2015	2018	£9,000	£9,250	High
2016	2019	£9,000		High
2017	2020	£9,000		High
2018	2021	£9,250		High

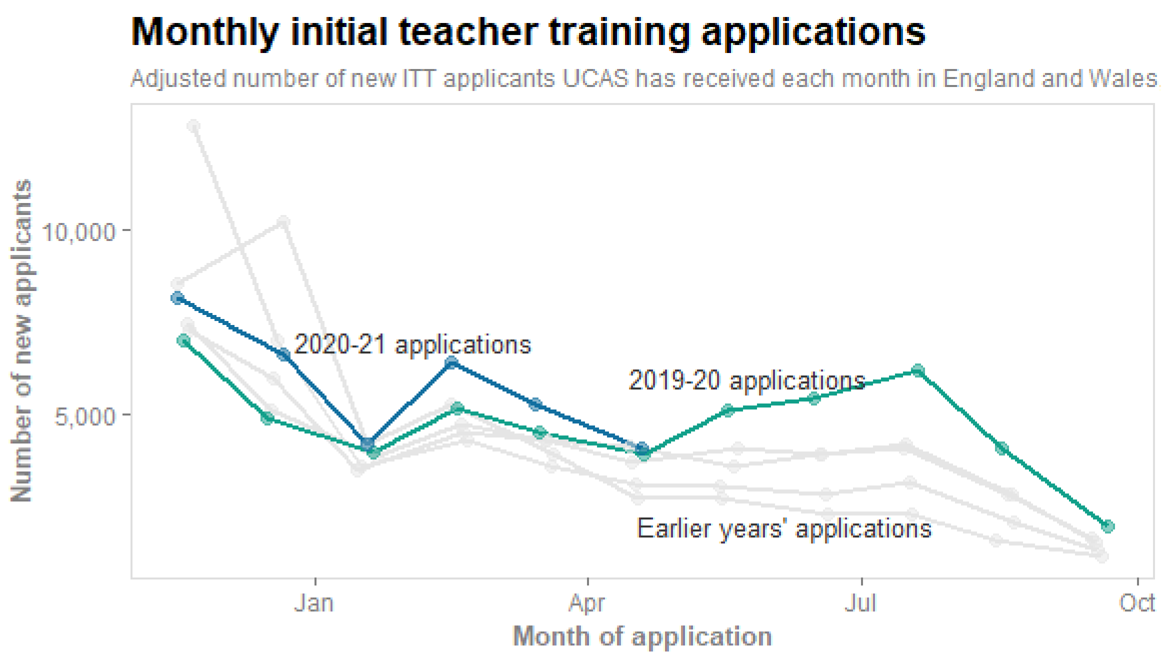
[+] This the first year an individual would be eligible to start a PGCE after they completed a three year undergraduate course. Also note that Tuition fees for the years prior to 2012 increased with inflation.

Appendix Table A2 Unemployment rate by field of study

	Mean (%)	Interquartile Range+ (%)	Range (%) (max – min)	kurtosis++	Skewness+++
Biological Sciences	2.66	1.04	1.77	1.95	-0.11
Physical Sciences	2.75	0.66	1.46	2.63	-0.12
Mathematical Sciences	3.26	2.87	3.68	1.38	0.21
Computer Sciences	3.86	1.71	5.37	3.99	0.93
Social Studies	2.90	0.44	0.89	1.95	-0.25
Languages	2.74	1.14	2.97	2.68	0.39
History/Philosophy	3.16	1.24	3.52	2.27	-0.02
Arts	4.00	1.36	4.82	3.39	1.05
Education	0.98	0.79	1.98	2.95	-0.24
Combined Degrees	0.84	1.62	3.43	2.92	1.10
All Degrees	3.02	0.99	7.20	5.49	0.88

+ p75-p25++ A normal distribution has a kurtosis of 3. Distributions with a kurtosis greater than 3 have heaver tails while a kurtosis less than 3 means the distribution has lighter tails +++ Measures the degree and direction of asymmetry in a distribution, a symmetric distribution has a skewness of 0. A distribution that is skewed to the left has a negative skewness, while a distribution skewed to the right has a positive skewness.

Figure A1



Source: UCAS ITT Statistics. UCAS statistical release occurs at uneven intervals. Note that the UCAS statistical release occurs at uneven intervals. We have adjusted for that by reporting 30.4*the average number of applications per day during the period which allows the points in the figure to be interpreted as if they were monthly.

Appendix Chapter 3

Appendix Table 1 shows the differences in observable characteristics between graduates who go into teaching and those who do not for the years 2000 (column a vs b) and 2010 (d vs e) and how using propensity score matching reduces the observable difference between teachers and non-teachers (a vs c and d vs f).

	(a)	(b)	(c)	(d)	(e)	(f)
		Year 2000			Year 2010	
Variable	Teachers	Non-Teachers		Teachers	Non-Teachers	
		Unmatched	Matched		Unmatched	Matched
Male	.417	.65***	.45*	.369	.588***	.381
White	.967	.928***	.968	.946	.869***	.933
Age	41.46	36.85***	42.08*	41.5	39.1***	42.2
Married	.669	.538***	.649	.626	.561***	.601
Region of Domicile:						
London	.117	.221***	.110	.118	.193***	.125
South East	.284	.310**	.295	.300	.281	.287
Degree Subjects:						
Medicine	.017	.082***	.017	.018	.101***	.015
Education	.414	.022***	.412	.437	.024***	.433
Mathematical Sciences	.151	.307***	.147	.137	.270***	.132
Biological Sciences	.062	.064	.067	.071	.079	.072
Social Sciences	.113	.369***	.117	.108	.380***	.107
Humanities	.186	.109***	.182	.168	.085***	.178
Art	.053	.042*	.052	.058	.045**	.059
n	1,573	6,400		1,459	7,409	

The starts indicate statistical significance in the difference in observable characteristics between the non-teachers (columns b, c and e,f) and teachers (columns a and d respectively)to the usual levels * p<0.10,**p<0.05,***p<0.01

The data source is the 2000 and 2010 labour force surveys. The sample is restricted to graduates who work full time and are between the ages of 21 and 65. Teachers (column a and d) are teachers who teach in a primary or secondary school. Non-teachers (column b,c and e,f) are defined are any non-teaching graduate.

Appendix Table 2 The impact of teachers wages on Grade 8 Scores in TIMSS

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
				Science							Math			
Log Teacher Wages	0.170 (0.268)	-0.0235 (0.286)	0.454 (0.341)					-0.674** (0.264)	-0.720*** (0.275)	0.390 (0.339)				
Log Non-Teacher Wages (Match)		0.226 (0.225)							0.0611 (0.324)					
Log Non-Teacher Wages (Normal)			-0.250 (0.181)							-0.955* (0.557)				
Wage Difference (Match)				-0.222* (0.113)							-0.0918 (0.118)			
Wage Difference (Normal)					0.236 (0.180)							0.987*** (0.187)		
Labor Market Returns to Teaching (Match)						-0.200* (0.115)							-0.0444 (0.121)	
Labor Market Returns to Teaching (Norm)							0.256+ (0.176)							1.056*** (0.186)
Constant	-1.087*** (0.0455)	-2.584*** (0.752)	0.584 (1.213)	-1.087*** (0.0454)	-1.086*** (0.0455)	-1.087*** (0.0454)	-1.086*** (0.0455)	-0.876*** (0.0415)	-1.280+ (0.789)	5.505*** (1.255)	-0.875*** (0.0415)	-0.878*** (0.0415)	-0.875*** (0.0415)	-0.877*** (0.0415)
N	17302	17302	17302	17302	17302	17302	17302	15177	15177	15177	15177	15177	15177	15177

Our Dependent variables are standardized to have a mean of 0 and a standard deviation of 1. Regression includes all of our controls, these are: class size, student age above median in months, student sex, books at home, computer in home, speak English at home, teacher sex, teacher experience, teacher age and year fixed effects. Standard errors in parentheses clustered at the classroom level while statistical significant is indicated by: +p<0.15,* p<0.10,**p<0.05,***p<0.01. . Note: standard errors obtained from bootstrap (500).

Appendix Table 3 The impact of teachers wages on Grade 8 Scores Excluding teachers with two or less years experiences in TIMSS

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
				Science							Math			
Log Teacher Wages	0.218	0.0464	0.553+					-0.630**	-0.871***	0.223				
	(0.302)	(0.316)	(0.365)					(0.306)	(0.316)	(0.351)				
Log Non-Teacher Wages (Match)		0.199							0.287					
		(0.229)							(0.355)					
Log Non-Teacher Wages (Normal)			-0.319							-0.820				
			(0.430)							(0.620)				
Wage Difference (Match)				-0.194+							-0.303**			
				(0.125)							(0.127)			
Wage Difference (Normal)					0.314*							0.830***		
					(0.189)							(0.190)		
Labor Market Returns to Teaching (Match)						-0.177							-0.223*	
						(0.125)							(0.129)	
Labor Market Returns to Teaching (Norm)							0.319*							0.987***
							(0.188)							(0.194)
Constant	-1.063***	-2.379***	1.070	-1.065***	-1.063***	-1.065***	-1.063***	-0.915***	-2.813***	4.565***	-0.914***	-0.915***	-0.914***	-0.914***
	(0.0527)	(0.833)	(1.274)	(0.0527)	(0.0528)	(0.0527)	(0.0528)	(0.0479)	(0.850)	(1.271)	(0.0480)	(0.0479)	(0.0480)	(0.0479)
N	14696	14696	14696	14696	14696	14696	14696	12901	12901	12901	12901	12901	12901	12901

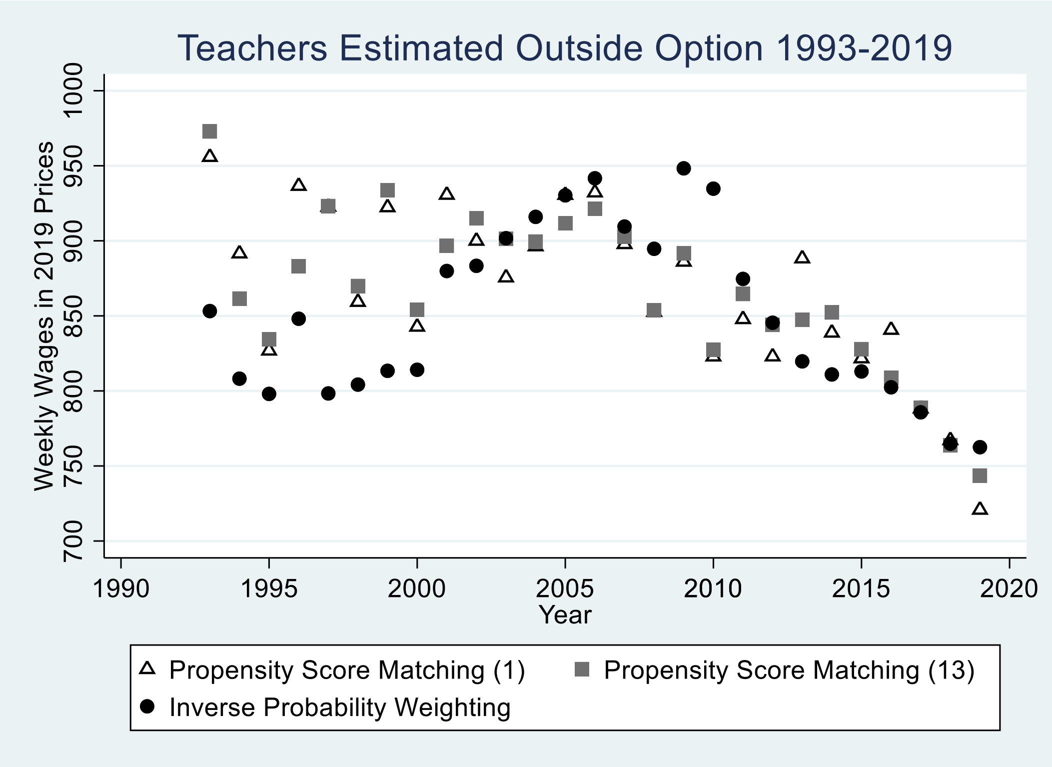
Our Dependent variables are standardized to have a mean of 0 and a standard deviation of 1. Regression includes all of our controls, these are: Class Size, Student Age above median in months, student sex, books at home, computer in home, speak English at home, teacher sex, teacher experience, teacher age and year fixed effects. Standard Errors in parentheses clustered at the classroom level while statistical significant is indicated by: +p<0.15,* p<0.10,**p<0.05,***p<0.01. Note: standard errors obtained from bootstrap (500)

Appendix Table 4 Effect of relative wages on Grade 8 pupil enjoyment in TIMSS

	1	2	3	4	5	6	7	8
	Science				Math			
Wage Difference (Match)	-0.0402 (0.0518)				0.0315 (0.0644)			
Wage Difference (Normal)		0.0204 (0.0960)				0.131 (0.105)		
Labor Market Returns to Teaching (Match)			-0.0430 (0.0518)				0.0469 (0.0652)	
Labor Market Returns to Teaching (Norm)				0.00885 (0.0935)				0.168+ (0.105)
Constant	0.680*** (0.0225)	0.680*** (0.0225)	0.680*** (0.0225)	0.680*** (0.0225)	0.607*** (0.0241)	0.606*** (0.0241)	0.607*** (0.0241)	0.606*** (0.0241)
DV mean (SD)	.745 (.435)	.745 (.435)	.745 (.435)	.745 (.435)	.640 (.480)	.640 (.480)	.640 (.480)	.640 (.480)
N	17156	17156	17156	17156	15060	15060	15060	15060

Regression includes all of our controls, these are: Class Size, Student Age above median in months, student sex, books at home, computer in home, speak English at home, teacher sex, teacher experience, teacher age and year fixed effects. Standard Errors in parentheses clustered at the classroom level while statistical significant is indicated by: +p<0.15,* p<0.10,**p<0.05,***p<0.01. . Note: standard errors obtained from bootstrap (500).

Appendix Figure 1 shows how the teachers' estimated outside option has changed using three different strategies. The black hollow triangle represents the estimates we use in this paper; these are calculated via nearest neighbour propensity score matching. The grey square is nearest neighbour propensity score matching, but slightly modified, as we increase the number of neighbours used to calculate the matched outcome to 13. Finally the filled black circle is teachers' outside option estimated using Inverse Probability Weighting.



Supplementary Material

Teachers Unemployment Rate

Specifically, we use the LFS to estimate the teachers' year and sex specific unemployment rate. This measure is the sum of unemployed individuals whose last job was teaching divided by the number of teachers plus the quantity of unemployed teachers. We estimate this separately by sex and year. Our measure of teacher unemployment only considers those who actually entered the teaching profession and therefore does not include those young people who want to go into teaching after they finished their training, but are unable to find a job. Although it is true that between 1 in 5 men and 1 in 10 women who finish teacher training do not to go into teachingthis does not mean that newly qualified teachers struggle to find a job as this is down to preferences and not employment opportunities. Each year roughly 3,000 more teachers leave the profession than enrol onto teacher training programmes. With pupil numbers increasing and more teachers leaving newly qualified teachers have extremely strong employment opportunities. Therefore any teacher unemployment we miss by using former teachers is unlikely to be significant. But if we measure teacher unemployment using qualified teachers we are likely picking up a lot of measurement error as many of these graduates may have never actually gone into teaching.

Teachers' unemployment rate tends to be around 1.7% and there are no meaningful gender differences. As the demand for teachers is driven by pupil numbers and policymakers desired pupil to teacher ratio we would not expect the teachers' unemployment rate to be affected by the financial crisis. However, we do observe that the unemployment rate rose above 2% between 2009 and 2012. We suspect this increase was driven by the fact that more than 50, mostly small rural Primary schools, closed during this period. It is important to note that the majority of the unemployment we observe among teachers is frictional as it is fairly unusual for teachers to get fired and the teachers who are affected by school closures tend to be amalgamated with another school. Similarly, we use the LFS to estimate the graduate unemployment rate by age, sex and year.

Teachers Relative Wages Descriptive Statistics using Merged Years

We have pupil performance data from the 1995, 2003, 2007, 2011 and 2015 TIMSS surveys. Additionally we are assigning each TIMSS teacher a teaching and non-teaching wage based on their sex (Male and Female) and age (measured in the following age bands: under 30, 30-39, 40-49, 50-59 and 60+). To achieve the required sample size we merge the LFS years together in the following way: the TIMSS 1995 teachers wages are estimated using LFS data from 1993 to 1996, 2003 uses 2001 to 2004, 2007 uses 2005 to 2008, 2011 uses 2009 to 2012 and 2015 uses 2013-2017.

Consistent with our estimates from the previous section teachers tend to earn less than the average graduate but table 1a column a shows that when we account for non-random selection the difference falls significantly (from 17% to 8% and 13% to 7% in 1995 and 2015 respectively) or dissipates entirely (2003, 2007 and 2011). Male teachers face a significant pay penalty for remaining in the occupation (Table 1b) while female teachers have considerable pecuniary benefits (Table 1c).

Comparing earnings of current teachers to former teachers we have no strong evidence that teachers who quit the occupation sort into higher paying occupations (table 2a) however now that we have the power to split this by gender we find that, actually, male teachers sort into occupations that are 9% (2011) and 11% (2015) higher paying.

Table 1a Ratio of teacher and non-teacher wages using a matching strategy (normal strategy). Using the combined sample of men and women.

	(a)	(b)	(c)	(d)	(e)	(f)
			Age Group			
Times Year	All	U30	30-39	40-49	50-59	60+
1995	0.922	1.028	0.920	0.819	1.034	0.964
	(0.837)	(0.845)	(0.783)	(0.780)	(0.833)	(0.921)
2003	1.018	1.039	0.998	0.963	1.034	1.155
	(0.870)	(0.859)	(0.804)	(0.846)	(0.868)	(1.112)
2007	1.027	1.115	1.030	0.996	1.064	1.148
	(0.884)	(0.901)	(0.814)	(0.773)	(0.885)	(1.060)
2011	1.003	1.217	1.045	0.939	1.005	1.143
	(0.900)	(0.980)	(0.876)	(0.792)	(0.882)	(1.063)
2015	0.934	1.171	1.019	0.854	0.931	0.990
	(0.865)	(0.959)	(0.867)	(0.781)	(0.821)	(0.921)

Our matching strategy is estimating teachers' outside option using propensity score matching by matching teachers to non-teacher graduates who are working full time. The variables we match on are: ethnicity, sex, age, marital status and region. The normal strategy that is reported in brackets is simply the ratio of teacher and non-teacher mean earnings. All of these differences are significant to the usual levels unless specified.

Table 1b Ratio of teacher and non-teacher wages using a matching strategy (normal strategy). Using a sample of only males.

	(a)	(b)	(c)	(d)	(e)	(f)
			Age Group			
Times Year	All	U30	30-39	40-49	50-59	60+
1995	0.852	0.997	0.865	0.694	0.996	0.869
	(0.842)	(0.927)	(0.780)	(0.785)	(0.832)	(0.922)
2003	0.963	0.952	0.923	0.937	0.983	1.170
	(0.851)	(0.881)	(0.784)	(0.743)	(0.852)	(1.108)
2007	0.966	1.098	0.959	0.903	0.995	1.127
	(0.857)	(0.934)	(0.786)	(0.741)	(0.862)	(1.069)
2011	0.928	1.108	0.935	0.883	0.944	1.098
	(0.879)	(0.969)	(0.845)	(0.797)	(0.858)	(1.063)
2015	0.896	0.914	0.932	0.845	0.889	1.004
	(0.845)	(0.950)	(0.834)	(0.789)	(0.799)	(0.935)

Our matching strategy is estimating teachers' outside option using propensity score matching by matching teachers to non-teacher graduates who are working full time. The variables we match on are: ethnicity, sex, age, marital status and region. The normal strategy that is reported in brackets is simply the non-teacher mean earnings. All of these differences are significant to the usual levels unless specified.

Table 1c Ratio of teacher and non-teacher wages using a matching strategy (normal strategy). Using a sample of only females.

	(a)	(b)	(c)	(d)	(e)	(f)
			Age Group			
Times Year	All	U30	30-39	40-49	50-59	60+
1995	1.015	1.007	0.987	1.041	1.124	1.050
	(0.959)	(0.964)	(0.873)	(0.955)	(1.073)	(1.050)
2003	1.060	1.121	1.078	0.988	1.084	1.370
	(1.008)	(1.012)	(0.908)	(0.881)	(1.047)	(1.288)
2007	1.098	1.060	1.078	1.063	1.139	1.217
	(1.012)	(1.009)	(0.908)	(0.934)	(0.893)	(1.130)
2011	1.095	1.303	1.134	1.028	1.085	1.159
	(1.026)	(1.091)	(0.983)	(0.888)	(1.035)	(1.179)
2015	0.973	1.263	1.093	0.874	0.965	1.031
	(0.979)	(1.069)	(0.972)	(0.860)	(0.958)	(1.068)

Our matching strategy is estimating teachers' outside option using propensity score matching by matching teachers to non-teacher graduates who are working full time. The variables we match on are: ethnicity, sex, age, marital status and region. The normal strategy that is reported in brackets is simply the non-teacher mean earnings. All of these differences are significant to the usual levels unless specified.

Table 2a Ratio of teacher and non-teaching qualified teachers wages using matching strategy (normal strategy) using a combined sample of both men and women by age group by year

	(a)	(b)	(c)	(d)	(e)	(f)
			Age Group			
Times Year	All	U30	30-39	40-49	50-59	60+
1995	1.086	1.079	1.051	1.061	1.077	1.343
	(1.048)	(0.870)	(1.021)	(1.058)	(1.106)	(1.343)
2003	1.066	1.051	1.138	1.045	1.046	1.051
	(1.013)	(1.025)	(1.060)	(1.023)	(1.057)	(1.123)
2007	1.136	1.181	1.146	1.138	1.117	1.082
	(1.042)	(1.076)	(1.051)	(1.100)	(1.102)	(1.064)
2011	1.070	1.243	1.137	0.961	1.004	1.135
	(0.957)	(1.143)	(1.057)	(0.928)	(1.332)	(1.135)
2015	0.985	1.156	1.050	0.970	0.950	1.082
	(0.920)	(1.128)	(1.005)	(0.976)	(0.940)	(0.975)

Our matching strategy is estimating teachers' outside option using propensity score matching by matching teachers to non-teacher graduates who are qualified to teach and are working full time. The variables we match on are: ethnicity, sex, age, marital status and region. The normal strategy that is reported in brackets is simply the non-teacher mean earnings. All of these differences are significant to the usual levels unless specified

Table 2b Ratio of teacher and non-teaching qualified teachers wages using matching strategy (normal strategy) by sex and year

	Sex		
Times Year	All	Male	Female
1995	1.086	1.042	1.101
	(1.048)	(1.059)	(1.062)
2003	1.066	1.020	1.076
	(1.013)	(1.015)	(1.040)
2007	1.136	1.060	1.178
	(1.042)	(1.014)	(1.0789)
2011	1.070	1.004	1.094
	(0.957)	(0.916)	(1.003)
2015	0.985	0.914	1.022
	(0.920)	(0.893)	(0.956)

Our matching strategy is estimating teachers' outside option using propensity score matching by matching teachers to non-teacher graduates who are qualified to teach and are working full time. The variables we match on are: ethnicity, sex, age, marital status and region. The normal strategy that is reported in brackets is simply the non-teacher mean earnings. All of these differences are significant to the usual levels unless specified.

If only pecuniary factors matter, what quitting rates would we observe?

Teachers in England have a high rate of attrition, especially young teachers - according to the 2018 School Workforce Census (SWC), of the teachers who started in 2016 1 in 4 quit within 24 months. The relatively limited empirical evidence on the determinants of teacher attrition (Smithers and Robinson 2003, Stinebrickner 1998) suggests it should be modelled as some combination of pecuniary and non-pecuniary factors (as in Manski (1987)). Indeed a simple econometric model of occupational choice is that teacher i will continue to teach at time t if her expected utility for remaining in teaching (j) is greater than, or equal to, her expected utility in her next best non-teaching alternative (j'). Where her expected utility is some function of pecuniary (w) and non-pecuniary (g) job specific characteristics. Formally:

1. $$Teach_{it} = \begin{cases} 1 \; if \; EU(w_{ijt}, g_{ijt}) \geq EU(w_{ij't}, g_{ij't}) \\ 0 \; if \; EU(w_{ijt}, g_{ijt}) < EU(w_{ij't}, g_{ij't}) \end{cases}$$

Policymakers have largely focused on using pecuniary factors to reduce teacher attrition; recent policies include restructuring teacher training bursaries into early career payments and a commitment to increasing teachers' initial wages to £30k a year. As our estimates suggest that young teachers already tend to earn more in teaching than they would in their outside option, and enjoy higher job security, it seems unlikely that pecuniary factors motivate attrition. However, the growth in teachers' wages is typically slower than their outside option. As a consequence the decline in relative wages over the lifecycle might, partially, explain the high rates of attrition in England. In this section, we estimate the probability that, for a given age and sex, a teacher who leaves the occupation would maximise their lifetime earnings using the following logit model:

2. $$Pr(Y_{ays} = 1 \mid X) = \phi(\beta_0 + \beta_1 X_1 + \epsilon_{ays})$$

Y_{ays} is a dummy that indicates if for age a, in year y and for sex s the Net Present Value (NPV) for teaching is lower than the NPV of their outside option. We calculate the NPV of teachers and non-teachers using estimates obtained from the LFS. Specifically the teachers' wages are the mean earnings of all teachers in England for a given age, year and sex while their non-teaching wage is the average non-teaching graduates earnings, controlling for differences in observable characteristics via propensity score matching, for a given age, year and sex. $\boldsymbol{X_1}$ is our vector of covariates, these are age (21-65), sex (Male vs Female) and year (1995, 2003, 2007, 2011, 2015).

To calculate the NPVs we assume that every teacher starts teaching at 21 and retires at 65 and their earnings over their lifecycle are the same as current teachers and non-teachers.[59] We are assuming that the unexplained component of teachers' wages is negatively correlated with the unexplained component of non-teachers' wages - teaching specific human capital is not rewarded on the labour market (Rickman and Parker 1990).

In addition, we are also assuming that there is no switching cost, a high (25%) or normal (12%) discount parameter, and that the market perfectly clears – they will be employed in teaching or non-

[59] For example in 2015 a 21 a female teacher earns £26kp.a, we will assume they will earn £34kp.a. when they turn 32, which is how much the average 32 year old female teacher earnt in 2015. We estimate the NPV separately by age (21-65), sex and year (1995, 2003, 2007, 2011, 2015).

teaching with a probability of 1.[60,61] Under these initial assumptions our estimates are intended to be interpreted as an upper bound.

Assuming a high (normal) discount parameter and perfect market clearance our logit estimates suggest that there is a 75% (77%) chance that male teachers could maximise their lifetime earnings by leaving teaching. While, consistent with the gender pay gap, we observe it is considerably less likely for female teachers (12% (9%)). The solid red line in figure 3 shows that the probability is highest for young teachers (88% (91%) for men and 21% (18%) for women) and lowest for those approaching retirement age (58% (57%) for men and 1%(3%) for women).

Relaxing our assumption on perfect market clearance and instead using the actual teacher and non-teacher unemployment rates we observe that the probability that a young teacher would be financially better off if they quit teaching falls - from 88% to 79% for men and 21% to 15% for women. As older graduates have a relatively low unemployment rate the impact of including employability on our estimates decreases with age to the extent that the probability for older teachers remains largely unchanged (see the green dot-dashed line vs the red solid line in Figure 3). If we impose a switching cost of 10% the probability does fall even more (from 75% to 60% for men and 12% to 6% for women), but even then there remains a high probability that young male teachers could maximise their lifetime earnings by quitting (see blue dashed line figure 3).

The probability that a male teacher would be financially better off if they left the profession exceeds 50% at almost every point over the lifecycle. Even if we assume a 40% switching cost, which is significantly larger than the impact of job displacement in our setting (Hijzen et al., 2010), we would still expect to observe an attrition rate of 33%. Yet, using the 2011 to 2018 SWC, we observe that male teachers' actual rate of attrition is between 9.5-10.7%. This large discrepancy suggests that male

[60] A discount parameter of 25% indicates that the value of getting £1 after one year and the £1 the year after has a net present value of £1.44 today (i.e. $\frac{1}{(1+0.25)^1} + \frac{1}{(1+0.25)^2} = 1.44$). While if we use a lower discount parameter (12%) the same income stream is worth £1.69 today (i.e. $\frac{1}{(1+0.12)^1} + \frac{1}{(1+0.12)^2} = 1.69$).

[61] Discounting rates tend to range between 10-14% (Meyer 2013) therefore we use the median (12%) as our normal discounting parameter. While our high discount rate is an arbitrary choice intended to show a scenario where individuals place a lot less significant on future earnings.

teachers hold strong teaching specific non-pecuniary preferences and/or they are considerably misinformed about their outside option.

In contrast, for female teachers' the actual rate of attrition (9-10%) is consistent with what we would expect to observe if female teachers were trying to maximise their lifetime earnings (6-12%). As the labour market has become more female friendly it could be that the historic female specific non-pecuniary benefits to teaching (such as compatibility with household production and fertility choices) might not be as unique to the profession today as they once were. As a consequence, the attrition of female teachers could be, in part, driven by a desire to maximise expected earnings.